



Artificial intelligence in shoulder arthroplasty: how smart is it?

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Background: The application of artificial intelligence (AI) is growing rapidly in many fields, and the medical field is no exception. The amount of information we collect before, during, and after surgery is growing exponentially, making the opportunity for AI applications to be integrated into our daily practice more and more apparent.

Methods: A literature search was conducted in January 2024 using PubMed (MEDLINE), SCOPUS, and EMBASE databases. A critical analysis of the relevant literature on AI technology in shoulder arthroplasty was conducted.

Results: In the field of shoulder arthroplasty, recent literature reports the predictive value of AI models in predicting length of hospital stay and health-care costs, predicting clinical outcomes and complications, and identifying implants. By leveraging machine learning before, during, and after surgery, surgeons can make clinical decisions, predict possible problems, estimate resources needed and clinical outcomes, and ultimately personalize care for each patient.

Conclusion: AI technology is becoming more and more advanced, especially in the medical field. By leveraging machine learning before, during, and after surgery, surgeons can make clinical decisions, predict possible problems, estimate resources needed and clinical outcomes, and ultimately personalize treatment for each patient. Because this technology is still in its infancy, there are several limitations to bringing it into the real-world clinical setting. However, it is advancing at a rapid pace, and therefore as a shoulder surgeon, you need to understand and be interested in AI technology.

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The use of artificial intelligence (AI) is growing rapidly in many industries, and health care is not an exception. AI is a term created by John McCarthy, who theorized the replication of human intelligence through computers.¹⁴ The modern definition of AI is the use of complex algorithms to solve problems without human cognition.^{15,35}

Once the stuff of science fiction movies, AI technology has become commonplace in everyday life, and many people would be surprised to learn how common it is in our daily lives. From the use of AI-powered “Google Search” features that predicted search patterns and preempted active searches 25 years ago, to social media advertisement (Facebook, Instagram), online purchase recommendation (Amazon), video streaming recommendations (Netflix), and

self-driving automobile (Tesla), AI technology is becoming an integral part of modern society. According to Gallup survey, 85% of Americans report using at least one AI-related product or service.⁹

While still in its infancy, the application of AI to orthopedics is an inevitable trend. While orthopedic surgeons have long been proud of their clinical skills and knowledge based on experience, we can no longer ignore the advances in technology that are occurring around the world. As the amount of information we collect before, during, and after surgery grows exponentially, there are more and more opportunities to integrate AI applications into our daily work. In addition, the need for AI technology is becoming more critical as innovative technologies such as navigation guides,¹⁶ robotic-assisted surgery²¹ and augmented reality guides^{22,39} are being developed.

The purpose of this review article is to provide the clinical orthopedic surgeon with a definition and basic understanding of AI, and to describe its use in orthopedic surgery, especially in the field of reverse total shoulder arthroplasty. This review also explores the limitations of current AI technologies and discusses future directions.

Institutional review board approval was not required for this narrative review.

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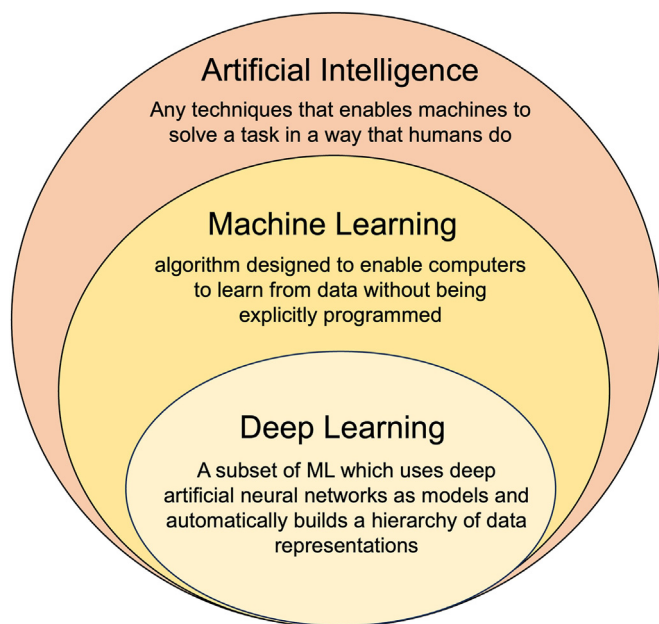


Figure 1 Comprehensive overview of artificial intelligence (AI) and its subfields.

What is artificial intelligence?

AI can be thought of as an umbrella term that encompasses a variety of subfields, including machine learning (ML), which includes a subfield called deep learning (DL).³⁵ (Fig. 1). AI refers to any technology that enables machines to perform tasks in a human-like manner. This includes tasks like planning, language understanding, pattern recognition, learning, and problem solving. The most important characteristic of AI is that it constantly changes its algorithms as it learns from its mistakes, which is similar to how humans learn.

Machine learning

ML was introduced shortly after AI as a way to achieve AI.³⁵ ML is an algorithm designed to help computers learn from data and improve their performance at specific tasks over time without being explicitly programmed. ML models are built using inputted features (data), which are divided into 2 separate groups: a training set, which is used to build the mathematical model, and a testing set, which is used to assess the model's performance. In ML, "learning" is done by tuning hyperparameters, such as the learning rate or choice of optimizer, which specifies details of the learning process, to optimize the model's performance.^{32,41}

Traditional statistics and ML represent distinct paradigms in data analysis.²⁷ Traditional statistics focuses on inferring population parameters from samples through probability-based methods, making assumptions about data distribution and emphasizing hypotheses testing. In contrast, ML builds algorithms to predict outcomes without explicit programming, with less concern for strict data distribution assumptions. Traditional statistics relies on theoretical model specification, exploring relationships and providing interpretable results. ML prioritizes prediction accuracy, sacrificing interpretability, and is often more robust to noise. Traditional statistics can work with any reasonable set, while ML requires big data (Table I).

The ML training process can either be supervised or unsupervised.⁸ In supervised learning, an algorithm is trained on a set of labeled data, and each example of the training data is paired with a

corresponding output or target variable.⁷ The algorithm learns the relationship between the input features and the target variable during the training process. For example, if an ML algorithm is tasked with predicting scapular notching after reverse total shoulder arthroplasty, dataset including input features (i.e., pre-operative range of motions, patient reported outcome measures, comorbidities, demographics, radiologic measurements etc.) and output labels (whether this patient has scapular notching or not) is required. With supervised ML, inaccurate labeling of data can lead to bias and error.

In contrast, in unsupervised learning, the algorithm is given data without explicit labels or target variables.^{1,23} The system must look for patterns, relationships, or structures within the data without any guidance on the output. The algorithm tries to find clustering or self-organization of the given data in a way that can give rise to so-called black box phenomena. The black box phenomenon occurs when an algorithm detects potentially anomalous patterns that are incomprehensible to human logic, making the results of a model's retrospective performance evaluation difficult for humans to understand.

Deep learning and neural networks

DL is a more sophisticated form of ML. DL can perform unsupervised learning on unstructured and unlabeled inputs and filter input data from variables that are less relevant to the prediction of interest. DL focuses on using artificial neural networks (ANNs), which are computational models inspired by the structure and function of the human brain. It consists of interconnected nodes, called neurons, organized in layers. Each connection between neurons has an associated weight, and each neuron applies an activation function to the weighted sum of its inputs.¹⁵ The depth of the network allows it to learn complex features and patterns, making DL particularly effective for tasks such as image and speech recognition, natural language processing, and more. Popular DL architectures include Convolutional Neural Networks for image-related tasks and Recurrent Neural Networks for sequence data.

AI in shoulder arthroplasty: where are we now?

While AI in orthopedics is still considered a new field, its application is growing in many areas (Fig. 2). The vast accumulation of patient data, patients' increasing expectations of postoperative outcomes, and surgeons' desire to improve postoperative outcomes have created many opportunities to leverage AI. In the field of shoulder arthroplasty in particular, recent literature reports the predictive value of AI models in predicting length of hospital stay (LOS) and health-care costs, predicting clinical outcomes and complications, and identifying implants (Table II).

Length of hospital stay (LOS) and health-care cost prediction

Using AI to predict postoperative LOS and health-care costs for patients undergoing shoulder arthroplasty can help optimize value-based care and develop patient-specific pricing for governments and insurance companies.^{3,13,19,30} Accurately predicting patient LOS allows hospitals to make the most efficient use of health-care resources when assigning inpatient beds.³⁷ It also allows surgeons to explain to patients before surgery the length and cost of their postoperative hospital stay. Predicting long-LOS patients can also be recognized and intervened upon early, allowing for faster recovery plans and providing better care. Predicting high-cost patients allows hospitals to devote additional resources to at-risk patients to prevent anticipated complications and reduce overall costs.

Table I
Difference between Machine Learning (ML) and statistics.

	Machine learning (ML)	Statistics
Subfield	Artificial Intelligence	Mathematics
Purpose	Optimization: Prediction accuracy	Inferences: Relationship between variables
Focus	Predict outcomes without explicit programming	Inferring population parameters, hypothesis testing
Data Size	Any Reasonable Set	Big Data
Interpretability	High	Low

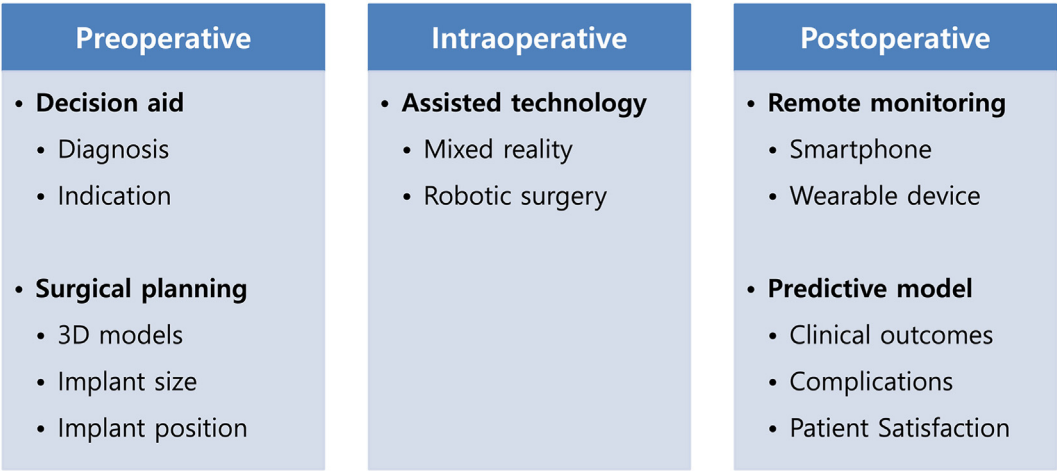


Figure 2 Possible applications of artificial intelligence in shoulder arthroplasty.

Table II
Literature review on the application of artificial intelligence in shoulder arthroplasty.

Author, year	Purpose	Input variable	Study population	Figure of merit
Gowd et al, 2022 ⁴	LOS and cost prediction	12 variables	ACS-NSQIP database 16,993 aTSA, 32,361 rTSA	AUC 0.66–0.87
Karnuta et al, 2020 ⁵	LOS and cost prediction	39 variables	NIS database 68,743 aTSA, 22,047 rTSA	Total cost: Accuracy 76.5%, AUC 0.75 LOS: Accuracy 91.8%, AUC 0.89
Biron et al, 2020 ¹	LOS prediction	13 variables	ACS-NSQIP database 4500 aTSA	AUC 0.77
Kumar et al, 2020 ⁷	Clinical outcome prediction	291 variables	Multicenter database 1895 aTSA, 2887 rTSA	MCID: Accuracy 90–95%, AUC 0.84–0.91
Kumar et al, 2021 ⁶	Clinical outcome prediction	19 variables	Multicenter database 2153 aTSA, 3621 rTSA	MCID: Accuracy 84–97%, AUC 0.72–0.94
McLendon et al, 2021 ⁹	Clinical outcome prediction	12 variables	Single-center database 431 aTSA, 41 rTSA	ASES score improvement: Accuracy 0.71 ~ 0.95
Polce et al, 2021 ¹⁰	Clinical outcome prediction	10 variables	Single-center database 225 aTSA, 188 rTSA	Satisfaction at postoperative 2 years: AUC 0.65 ~ 0.8
Gowd et al, 2019 ³	Complication prediction	22 variables	ACS-NSQIP database 17,119 TSA	Any adverse effect: Accuracy 92.1–95.4%
Geng et al, 2023 ²	Implant identification	10 implants	Single-center database 696 TSA	Accuracy 93.9%
Kunze et al, 2023 ⁸	Implant identification	22 implants	Multicenter database 3060 TSA	Accuracy 97.1%, AUC 0.994 ~ 1.000
Yi et al, 2020 ¹¹	Implant identification	5 implants	Multicenter database 482 TSA	Distinguish between aTSA vs rTSA: AUC 0.97 Classify 5 specific TSA models: AUC 0.86 ~ 1.0

LOS, Length of Hospital Stay; ACS-NSQIP, The American College of Surgeons National Surgical Quality Improvement Program; NIS, National Inpatient Sample; ASES, American Shoulder and Elbow Surgeons; aTSA, Anatomic total shoulder arthroplasty; rTSA, Reverse total shoulder arthroplasty; AUC, Area under curve; MCID; Minimal clinically important difference.

Karnuta et al reviewed 111,147 patients undergoing primary shoulder replacement and developed an ML model using 39 pre-operative variables to predict LOS, discharge disposition, and inpatient charges for primary anatomical total, reverse total, and hemi-shoulder arthroplasty. ML algorithm achieved accuracies of 76.5%, 91.8% and 73.1% for total cost, LOS, and disposition, respectively.¹⁹ Another similar study has also developed ML model using random forest algorithm predicting short stay or outpatient

shoulder arthroplasty and reported fair diagnostic performance with area under curve of 0.77.³

Outcome prediction

The performance of ML in predicting patient outcomes after shoulder arthroplasty has been published by several authors.^{24,25,33,36,38} Outcome prediction can help in the

collaborative decision-making process between the orthopedic surgeon and the patient, especially in determining whether the procedure meets the patient's expectations. Early identification of patients who will have low postoperative patient-reported outcome measures (PROMs) also allows for closer postoperative patient follow-up and optimizes preoperative decision-making.

Several studies have developed models to predict the minimum clinically important difference after surgery, which is the amount of improvement in PROMs needed for a patient to judge that they have improved after surgery. ML algorithms developed by Kumar et al were shown to have fair to good performance to predict 1 to 5 year postoperative minimum clinically important difference for shoulder specific PROMs and range of motion.²⁵ They also compared the accuracy with full model comprising 291 parameters and minimal-feature set model comprising 19 features to predict clinical outcomes after shoulder arthroplasty. Results showed that the full and abbreviated models achieved similar accuracy in predicting clinical outcomes.²⁴ Another outcome measure used to evaluate the efficacy and value of the intervention is postoperative patient satisfaction. Recent study by Polce et al also found that supervised ML was able to predict satisfaction at 2 years following total shoulder arthroplasty with 10 preoperative variables, so that it could help in optimizing preoperative health, improving patient selection, education, and satisfaction.³⁶

Gowd et al did a retrospective cohort study of 17,119 patients undergoing total shoulder arthroplasty.¹² They developed a supervised ML algorithms in predicting complications, including transfusion, extended LOS, surgical site infection, return to the operating room, deep vein thrombosis or pulmonary embolism. Each ML algorithm was compared with one another and with baseline model using American Society of Anesthesiologists classification. ML algorithms outperformed American Society of Anesthesiologists classification for predicting complications. Accurate prognostic information obtained by this algorithm can aid preoperative decision-making and enhance postoperative care.

Implant identification

When planning revision surgery for a patient who had primary surgery at another hospital, it is important to identify the manufacturer and type of implant, but this could be difficult to identify for some instance. DL algorithm has been shown good to excellent performance to recognize implant manufacturer and design in shoulder arthroplasty.^{10,26,42} A recent study by Kunze et al showed that their DL algorithm was able to distinguish between 22 different reverse and anatomic shoulder prosthesis from eight implant manufacturers with 97.1% accuracy and AUROC of 0.994–1.000 simply by evaluating single anteroposterior view radiograph image.²⁶

AI in shoulder arthroplasty: what is expected in future?

Rehabilitation and postoperative care

Newer technologies to monitor and improve rehabilitation after shoulder arthroplasty will provide more objective outcome measures compared to traditional patient-reported activity questionnaires. Wearable devices can record the movement profile of patients postoperatively, which can be used to assess their functional recovery.^{2,4} Continuous data from the device can be analyzed by ML algorithms which can lead to reliable measurement of functional outcomes after shoulder arthroplasty. Furthermore, surgeons could also evaluate rehabilitation compliance of patients after surgery. Chen et al applied a wearable motion sensor device to assist patients conduct home-based exercises to improve training

compliance and the accuracy of exercises for patients with adhesive capsulitis of shoulder.⁵ Motion sensor-assisted rehabilitation group exhibited better shoulder mobility and functional recovery and higher exercise completion rate than home-based exercise group.

AI for surgical robotics

Robotic-assisted surgery improves surgeons' ability to perform more precise and accurate surgeries more consistently, following a patient-specific plan.¹⁸ AI can improve the ability of surgical robotic systems to recognize complex environments, make predictions, make decisions, and perform desired tasks with improved precision, safety, and efficiency, with or without human control.

Orthopedic robotic platforms have grown substantially in popularity in recent years, with several different commercially available systems currently being used for hip and knee joint replacement in clinical practice.^{6,28} In shoulder arthroplasty, it is thought that such a system would help to accurately prepare the bone and precisely cut the humeral head to place the implant in an optimal position, but no such system exists yet.

Clinical decision making

By leveraging AI's ability to process and optimize large, complex data sets, surgeons can select patients who need surgery, create patient-specific surgical plans, predict clinical outcomes and implant survival, and identify patients at high risk for complications.³¹ Especially, choosing the surgical strategy that will result in the best clinical outcome is an unsolved problem for shoulder surgeons. For example, whether to do a total or reverse shoulder arthroplasty, whether to choose a medialized or lateralized glenoid and humeral implant, the optimal glenoid version, inclination, and humeral retroversion for each patient, and optimal joint tension are still controversial topics. Given the rapid technological advancements, it is expected that in the future, AI technologies will be able to analyze large volumes of data with a high degree of precision to support better personalized decision-making processes.

Limitation of AI

While AI appears to be omniscient, there are currently limitations to its application. Because the data it is trained on may not be representative of the entire population, developed ML can introduce bias in practice settings other than the one it was developed in.⁴⁰ Training data should be representative of the general population independently from gender, race, and cultural and economic backgrounds.²⁹ To avoid bias in the algorithm, the data it is trained on should be multinational and multicenter data that is well representative of the population, and once the algorithm is developed, it should be validated on a sample population in the region where it will actually be used.²⁰

Sharing data across organizations to ensure that Train data is representative of the population can lead to privacy and data protection issues. What if a ML algorithm was used as a proxy for determining surgeon competence, licensure and credentialing? This prospect is likely to stimulate interest in the ensuring the appropriate and secure development and training of ML algorithms. AI developers need to protect personal information and other information that could harm patients.¹¹ There are also unique challenges and risks associated with cybersecurity threats.³⁷

Black-box and responsibility are other issues.^{11,34} Some ML algorithms have a black box phenomenon, a characteristic that makes it difficult to logically explain how an algorithm's predictions are generated. Additionally, there are no laws in place to determine medical liability in the event of misjudgment.¹⁷ If an

algorithm can't explain why and how it makes certain decisions, it's hard to gain trust with patients, and it can be difficult to get their consent to use AI.³⁴ Explainable and interpretable algorithms are necessary not only to detect bias, but also to build transparent and trustworthy AI systems.^{11,34}

Conclusions

Along with other technological advancements, AI technology is becoming more and more advanced, especially in the medical field. Numerous papers have been reported utilizing AI in the field of shoulder arthroplasty. By leveraging ML before, during, and after surgery, surgeons can make clinical decisions, predict possible problems, estimate resources needed and clinical outcomes, and ultimately personalize treatment for each patient. Because this technology is still in its infancy, there are several limitations to bringing it into the real-world clinical setting. However, it is advancing at a rapid pace, and therefore as a shoulder surgeon, you need to understand and be interested in AI technology.

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References

- Baessler AM, Brolin TJ, Azar FM, Sen S, Chang M, Falkner D, et al. Development and validation of a predictive model for outcomes in shoulder arthroplasty: a multicenter analysis of nearly 2000 patients. *J Shoulder Elbow Surg* 2021;30:2698–702. <https://doi.org/10.1016/j.jse.2021.06.007>.
- Beshara P, Chen JF, Read AC, Lagadec P, Wang T, Walsh WR. The reliability and validity of wearable inertial sensors coupled with the microsoft kinect to measure shoulder range-of-motion. *Sensors* 2020;20:7238. <https://doi.org/10.3390/s20247238>.
- 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>.
- Chan LYT, Chua CS, Chou SM, Seah RYB, Huang Y, Luo Y, et al. Assessment of shoulder range of motion using a commercially available wearable sensor—a validation study. *mHealth* 2022;8:30. <https://doi.org/10.2196/mhealth-22-7>.
- Chen YP, Lin CY, Tsai MJ, Chuang TY, Lee OK. Wearable motion sensor device to facilitate rehabilitation in patients with shoulder adhesive capsulitis: pilot study to assess feasibility. *J Med Internet Res* 2020;22:e17032. <https://doi.org/10.2196/17032>.
- D'Souza M, Gendreau J, Feng A, Kim LH, Ho AL, Veeravagu A. Robotic-assisted spine surgery: history, efficacy, cost, and future trends. *Robot Surg* 2019;6:9–23. <https://doi.org/10.2147/rsrr.S190720>.
- Farrow L, Zhong M, Ashcroft GP, Anderson L, Meek RMD. Interpretation and reporting of predictive or diagnostic machine-learning research in Trauma & Orthopaedics. *Bone Joint Lett J* 2021;103-b:1754–8. <https://doi.org/10.1302/0301-620x.103b12.Bjj-2021-0851.R1>.
- Galbusera F, Casaroli G, Bassani T. Artificial intelligence and machine learning in spine research. *JOR Spine* 2019;2:e1044. <https://doi.org/10.1002/jsp2.1044>.
- Gallup, Northeastern University. Optimism and anxiety: views on the impact of artificial intelligence and higher education's response [cited 2023 Dec 6]. Available from: <https://news.gallup.com/reports/226475/gallup-northeastern-university-artificial-intelligence-report-2018.aspx>.
- Geng EA, Cho BH, Valliani AA, Arvind V, Patel AV, Cho SK, et al. Development of a machine learning algorithm to identify total and reverse shoulder arthroplasty implants from X-ray images. *J Orthop* 2023;35:74–8. <https://doi.org/10.1016/j.jor.2022.11.004>.
- Gerke S, Minssen T, Cohen G. Ethical and legal challenges of artificial intelligence-driven healthcare. In: *Artificial intelligence in healthcare*; 2020. p. 295–336.
- 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>.
- Gowd AK, Agarwalla A, Beck EC, Rosas S, Waterman BR, Romeo AA, et al. Prediction of total healthcare cost following total shoulder arthroplasty utilizing machine learning. *J Shoulder Elbow Surg* 2022;31:2449–56. <https://doi.org/10.1016/j.jse.2022.07.013>.
- Han XG, Tian W. Artificial intelligence in orthopedic surgery: current state and future perspective. *Chin Med J (Engl)* 2019;132:2521–3. <https://doi.org/10.1097/cm9.0000000000000479>.
- Hashimoto DA, Rosman G, Rus D, Meireles OR. Artificial intelligence in surgery: promises and perils. *Ann Surg* 2018;268:70–6. <https://doi.org/10.1097/sla.0000000000002693>.
- Holzgreffe RE, Hao KA, Panther EJ, Schoch BS, Roche CP, King JJ, et al. Early clinical outcomes following navigation-assisted baseplate fixation in reverse total shoulder arthroplasty: a matched cohort study. *J Shoulder Elbow Surg* 2023;32:302–9. <https://doi.org/10.1016/j.jse.2022.07.007>.
- Innocenti B, Radyul Y, Bori E. The use of artificial intelligence in orthopedics: applications and limitations of machine learning in diagnosis and prediction. *App Sci* 2022;12:10775. <https://doi.org/10.3390/app122110775>.
- Jacofsky DJ, Allen M. Robotics in arthroplasty: a comprehensive review. *J Arthroplasty* 2016;31:2353–63. <https://doi.org/10.1016/j.arth.2016.05.026>.
- 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>.
- Kelly CJ, Karthikesalingam A, Suleyman M, Corrado G, King D. Key challenges for delivering clinical impact with artificial intelligence. *BMC Med* 2019;17:195. <https://doi.org/10.1186/s12916-019-1426-2>.
- Khlopas A, Sodhi N, Sultan AA, Chughtai M, Molloy RM, Mont MA. Robotic Arm-assisted total knee arthroplasty. *J Arthroplasty* 2018;33:2002–6. <https://doi.org/10.1016/j.arth.2018.01.060>.
- Kriechling P, Loucas R, Loucas M, Casari F, Furnstahl P, Wieser K. Augmented reality through head-mounted display for navigation of baseplate component placement in reverse total shoulder arthroplasty: a cadaveric study. *Arch Orthop Trauma Surg* 2023;143:169–75. <https://doi.org/10.1007/s00402-021-04025-5>.
- Kumar V, Patel S, Baburaj V, Vardhan A, Singh PK, Vaishya R. Current understanding on artificial intelligence and machine learning in orthopaedics - a scoping review. *J Orthop* 2022;34:201–6. <https://doi.org/10.1016/j.jor.2022.08.020>.
- Kumar V, Roche C, Overman S, Simovitch R, Flurin PH, 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>.
- Kumar V, Roche C, Overman S, Simovitch R, Flurin PH, Wright T, et al. What is the accuracy of three different machine learning techniques to predict clinical outcomes after shoulder arthroplasty? *Clin Orthop Relat Res* 2020;478:2351–63. <https://doi.org/10.1097/cor.0000000000001263>.
- Kunze KN, Jang SJ, Li TY, Pareek A, Finocchiario A, Fu MC, et al. Artificial intelligence for automated identification of total shoulder arthroplasty implants. *J Shoulder Elbow Surg* 2023;32:2115–22. <https://doi.org/10.1016/j.jse.2023.03.028>.
- Ley C, Martin RK, Pareek A, Groll A, Seil R, Tischer T. Machine learning and conventional statistics: making sense of the differences. *Knee Surg Sports Traumatol Arthrosc* 2022;30:753–7. <https://doi.org/10.1007/s00167-022-06896-6>.
- Li C, Wang L, Perka C, Trampuz A. Clinical application of robotic orthopedic surgery: a bibliometric study. *BMC Musculoskelet Disord* 2021;22:968. <https://doi.org/10.1186/s12891-021-04714-7>.
- Lisacek-Kiosoglous AB, Powling AS, Fontalis A, Gabr A, Mazomenos E, Haddad FS. Artificial intelligence in orthopaedic surgery. *Bone Joint Res* 2023;12:447–54. <https://doi.org/10.1302/2046-3758.127.BJR-2023-0111.R1>.
- Lopez CD, Constant M, Anderson MJ, Confinio 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>.
- Magan AA, Kayani B, Chang JS, Roussot M, Moriarty P, Haddad FS. Artificial intelligence and surgical innovation: lower limb arthroplasty. *Br J Hosp Med* 2020;81:1–7. <https://doi.org/10.12968/hmed.2020.0309>.
- McCelland C. The difference between artificial intelligence, machine learning, and deep learning [cited 2023 Dec 6]. Available from: <https://medium.com/iotforall/the-difference-between-artificial-intelligence-machine-learning-and-deeplearning-3aa67bff5991>.
- 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>.
- Morley J, Machado CCV, Burr C, Cows J, Joshi I, Taddeo M, et al. The ethics of AI in health care: a mapping review. *Soc Sci Med* 2020;260, 113172. <https://doi.org/10.1016/j.socscimed.2020.113172>.
- Myers TG, Ramkumar PN, Ricciardi BF, Urish KL, Kipper J, Ketosis C. Artificial intelligence and orthopaedics: an introduction for clinicians. *J Bone Joint Surg Am* 2020;102:830–40. <https://doi.org/10.2106/jbjs.19.01128>.
- 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>.
- Purnomo G, Yeo SJ, Liow MHL. Artificial intelligence in arthroplasty. *Arthroplasty* 2021;3:37. <https://doi.org/10.1186/s42836-021-00095-3>.

38. 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>.
39. Rojas JT, Jost B, Zipeto C, Budassi P, Zumstein MA. Glenoid component placement in reverse shoulder arthroplasty assisted with augmented reality through a head-mounted display leads to low deviation between planned and post-operative parameters. *J Shoulder Elbow Surg* 2023;32:e587–96. <https://doi.org/10.1016/j.jse.2023.05.002>.
40. Safdar NM, Banja JD, Meltzer CC. Ethical considerations in artificial intelligence. *Eur J Radiol* 2020;122:108768. <https://doi.org/10.1016/j.ejrad.2019.108768>.
41. Scarlat A. A machine learning primer for clinicians-part 1 [cited 2023 Dec 6]. Available from: <https://histalk2.com/2018/10/17/a-machine-learningprimer-for-clinicians-part>.
42. Yi PH, Kim TK, Wei J, Li X, Hager GD, Sair HI, et al. Automated detection and classification of shoulder arthroplasty models using deep learning. *Skeletal Radiol* 2020;49:1623–32. <https://doi.org/10.1007/s00256-020-03463-3>.