Sports Medicine and Artificial Intelligence

CME

A Primer

Prem N. Ramkumar,*†‡ MD, MBA, Bryan C. Luu,†§ BS, Heather S. Haeberle,†|| MD, Jaret M. Karnuta,† MS, Benedict U. Nwachukwu,|| MD, MBA, and Riley J. Williams,|| MD
Investigation performed at the Cleveland Clinic, Cleveland, Ohio, USA

Artificial intelligence (AI) represents the fourth industrial revolution and the next frontier in medicine poised to transform the field of orthopaedics and sports medicine, though widespread understanding of the fundamental principles and adoption of applications remain nascent. Recent research efforts into implementation of AI in the field of orthopaedic surgery and sports medicine have demonstrated great promise in predicting athlete injury risk, interpreting advanced imaging, evaluating patient-reported outcomes, reporting value-based metrics, and augmenting the patient experience. Not unlike the recent emphasis thrust upon physicians to understand the business of medicine, the future practice of sports medicine specialists will require a fundamental working knowledge of the strengths, limitations, and applications of AI-based tools. With appreciation, caution, and experience applying AI to sports medicine, the potential to automate tasks and improve data-driven insights may be realized to fundamentally improve patient care. In this Current Concepts review, we discuss the definitions, strengths, limitations, and applications of AI from the current literature as it relates to orthopaedic sports medicine.

Keywords: artificial intelligence; machine learning; deep learning; prediction

The application of artificial intelligence (AI) in the field of medicine has been widely forecasted since the term was first coined by John McCarthy over 60 years ago.[24] Despite initial excitement over the possibilities of AI in medicine, practical applications have only recently begun to materialize. In the field of orthopaedics and sports medicine, AI technology is still in its nascence, with few studies detailing potential future applications. These studies mainly center on the development of machine learning (ML) algorithms that serve as predictive models. Some examples of the utility of ML in orthopaedics include the identification of fractures from radiographic images, the ability to identify orthopaedic implants for the purpose of facilitating hardware removal and/or revision,[1,8,13,14,19,50] the prediction of postoperative opioid use after total hip arthroplasty,[14] and the evaluation of remote monitoring systems.[35] A 2018 systematic review demonstrated a recent increase in applications of ML in the field of orthopaedics.[5] This study found that the largest number of reports are focused on osteoarthritis detection and prediction, bone and cartilage imaging, and spine pathology detection. In general, the maturity of AI in the field of orthopaedics has lagged behind fields such as radiology, dermatology, and ophthalmology. While this is likely due to the hands-on nature of sports medicine, such as a nuanced physical examination and meticulous soft tissue handling, early applications of AI in sports medicine are increasingly more commonplace, with early emphasis on automated image analysis and risk stratification.

DEFINITIONS

Broadly, AI is the science and engineering of creating intelligent machines that have the ability to achieve tasks that otherwise require human input.[11] ML is a subset of AI that

*Address correspondence to Prem N. Ramkumar, MD, MBA, Orthopaedic Machine Learning Laboratory, Cleveland Clinic, 9500 Euclid Ave, Cleveland, OH 44118, USA (email: premramkumar@gmail.com) (@prem_ramkumar; @CleClinicMD).

†Orthopaedic Machine Learning Laboratory, Cleveland Clinic, Cleveland, Ohio, USA.

‡Department of Orthopaedic Surgery, Brigham and Women's Hospital, Boston, Massachusetts, USA.

§Department of Orthopaedic Surgery, Baylor College of Medicine, Houston, Texas, USA.

||Department of Orthopedic Surgery, Hospital for Special Surgery, New York, New York, USA.

Submitted July 15, 2020; accepted December 15, 2020.

One or more of the authors has declared the following potential conflict of interest or source of funding: B.U.N. has received education and hospitality payments from Smith & Nephew; hospitality payments from Zimmer Biomet Holdings, Wright Medical, and Stryker; and education and grant payments from Arthrex. R.J.W. has received consulting fees, hospitality payments, royalties, and nonconsulting fees from Arthrex and hospitality payments from Stryker. R.J.W., B.U.N., and P.N.R. are advisory board members of FocusMotion. AOSSM checks author disclosures against the Open Payments Database (OPD). AOSSM has not conducted an independent investigation on the OPD and disclaims any liability or responsibility relating thereto.

The American Journal of Sports Medicine
2022;50(4):1166–1174
DOI: 10.1177/03635465211008648

uses computational algorithms to analyze large data sets to classify, predict, or gain useful inference without explicit instructions.[10,11] In its most rudimentary form, ML models are given inputs and outputs of "training sets" using real-world data to determine relationships using pattern recognition.[10] As such, the model is dependent on the accuracy and biases of the given data set. The models are then tasked with creating predictions based on inputs from a "testing set," and these predictions are compared with known outcomes to quantify and refine the accuracy of the algorithm with positive or negative reinforcement. These algorithms possess the capacity to continually assess and improve the quality of their analyses when given an adequate volume of data inputs, with the potential to continue learning after implementation as new data become available.[10,11,28] Thus, the predictive power and accuracy of an ML algorithm are only as powerful as its training experience and volume, not unlike the expertise and judgment of a sports medicine specialist. Over 15 ML approaches exist and can be divided into supervised or unsupervised learning. Supervised learning encompasses a trial-and-error process by which the algorithm compares predictions with correctly labeled outputs in the training set. Unsupervised algorithms autonomously search for patterns without requiring correctly labeled outputs in the training set.

Expert systems, an early investigation into AI, are programs designed to mimic the decision making of an "expert" in a given field. These programs are built on knowledge bases that contain structured, factual deductions and heuristics. An expert system trains on these data and attempts to draw inferences and relationships, creating "rules" for future decision making. As an example, a high-volume experienced hip arthroscopy surgeon may provide a database with his or her case series of 150 patients associated with demographic and radiographic features and an "outcome" of primary labral repair versus labral reconstruction. The program would then have the capability of predicting the correct treatment for new cases based off of demographic and radiographic inputs. Despite the limited number of data points available, the architecture favors the "expert" data to trust the outcomes as more fixed ground truths for future predictions. Expert systems have been employed in natural language processing,[49] drastically decreasing the time required for administrative tasks for surgeons, such as chart review in an increasingly expansive electronic medical record.

Logistic regression represents a basic, widely accepted form of ML utilizing a logistic function to predict a binary response variable. Such an analysis is useful in predicting the probability of events with 2 possible outcomes, such as reaching the minimal clinically important difference of a patient-reported outcome within a specified time frame after an arthroscopic procedure. This algorithm is considered a rudimentary but reproducible standard to compare the performance of more advanced models.

Bayesian networks are probabilistic graphical models that revolve around Bayesian inference. They represent probability distributions of an outcome as a product of local, conditional probability distributions of discrete variables. These models help visualize and understand the relationships between variables and outcome. For example, given an athlete's current performance metrics and injury history, a constructed Bayesian network could provide a list of reinjury risk probabilities and anticipated performance metrics. These networks can also be used to reduce the administrative burdens of physicians. In one study, Navarro et al[29] trained a Bayesian model to preoperatively risk stratify patients undergoing total knee arthroplasty. From this model, the authors proposed a tiered patient-specific payment model, creating a payment model that more closely relates patient complexity to equitable reimbursement.

Random forest algorithms are used for tasks in regression (ie, predicting a numeric variable) and classification (ie, predicting a categorical variable). These algorithms create a multitude of "decision trees," flowchart-like structures in which a final outcome is reached as a result of choices made at several branching decision points. For example, if an elite athlete were to receive multiple opinions on a treatment modality at a critical juncture in his or her season, a random forest behaves as the summation of the most commonly agreed-upon decision across multiple opinions, while weighting the most important factors in the decision-making process from treatment invasiveness to convalescence timetable.

Support vector machines represent another form of supervised learning used for regression and classification tasks. This algorithm is characterized by the calculation of a multidimensional representation of the data as points in space, mapped such that separate categories are divided by as clear a gap as possible. This multidimensional "hyperplane" can then be used as a guide to classify new objects that fall on either side of the divide to lend to a prediction closest to the training set.

Artificial and deep neural networks embody deep learning, a subset of ML, and represent more sophisticated algorithms that require minimal to no human supervision for development. These models can mimic the structure and function of the biological neuronal brain. Unlike traditional, supervised ML algorithms, which generally require human expertise and the predetermined transformation of raw data into a suitable format, deep learning models are a form of representation learning and require minimal reformatting.[7] They work autonomously, allowing the system to discover alternative representations with differing levels of abstractions (Figure 1).

The neural network begins with an input tier that receives the raw data. The network then progresses to a number of "hidden tiers" that each responds to different features of the input.[27] A deep neural network is a subtype of artificial neural networks with at least 1 hidden tier. Through this process of developing multiple hidden layers, the model continues to develop more and more abstract representations of the data. Similar to the way that the human brain functions, the machine is able to make "neuronal" connections from "dendrites" on multiple hierarchical data levels.[11] Eventually, the model learns to appreciate a concept on multiple layers and dimensions, building upon itself to create a web of interconnected relationships.[10]

Overall, each type of ML algorithm has specific clinical scenarios that favor its use, depending on the type of

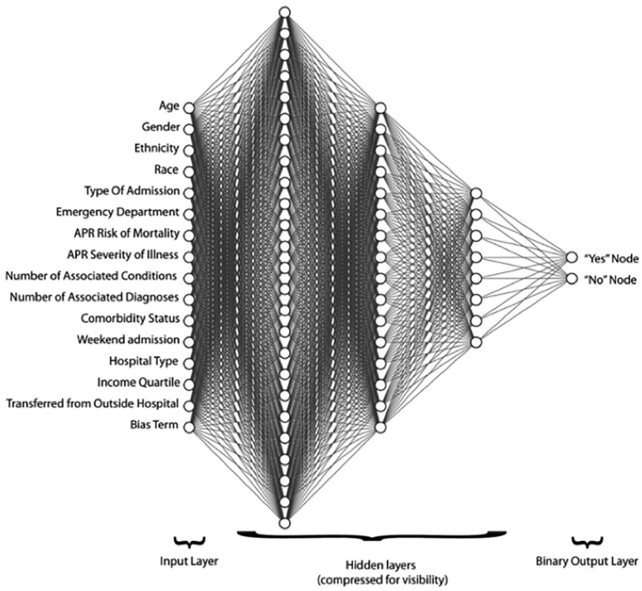

Figure 1. Diagram representing an artificial neural network model, demonstrating inputs, hidden layers, and binary outputs (''yes'' or ''no''), used to predict value-based outcomes (cost, length of stay, disposition) after any given inpatient procedure. APR, all patient refined.

inputs and outputs (ie, continuous vs discrete, numeric vs categorical).

CONTEXT

Human innovation has not demonstrated steady, continuous progress. Rather, we have seen long durations of relative technologic stasis, punctuated by periods of dramatic, dynamic growth. In recent history, experts recognize 3 distinct industrial revolutions, in which key discoveries catalyzed major transformation of human culture and economy.[23,24] The first industrial revolution began in 1760 with the development of the steam engine, enabling rapid development of new modes of transportation and a shift from hand production to machine-assisted manufacturing. The second industrial revolution, which began around 1870, centered on energy in the form of electricity and petroleum. Around 1970, the third industrial revolution was synonymous with the development of the computer and major advances in microprocessor design and raw computing power.[23] These 3 revolutions share a common theme: in each, key initial discoveries created new possibilities. Similarly, AI likely represents the fourth industrial revolution, a digital automation tool that may open doors previously unseen.[24,42]

Similarly, the role of the physician is constantly evolving—particularly sports medicine specialists, who are tasked with medical management and coordination of patients' expectations, injury severity, rehabilitation experts, and team personnel. At each junction, the profession has adjusted, reflecting the role that best serves patients at that time. One such transition point is the digitization of medicine, as new technologies (ie, advanced imaging, telemedicine encounters, electronic health records [EHRs], and wearable sensors) have engendered a tremendous volume of personalized, portable, and immediately accessible objective data into a previously data scarce field that relied on individual clinician intuition. Another transition point can be described as the democratization of medicine.[44] Previously, doctors were the sole gatekeepers of medical knowledge, which was made available to only the select few who had the means and ability to attend medical school. The democratization of medicine represents the liberation of this information, much of which is now widely available through online resources. Democratization also refers to the increase in patient empowerment, with doctors now tasked with working with patients and collaboratively reaching a treatment decision that is consistent with a patient's values and priorities.[44] While digitization and democratization are still in progress, these phases lend to the next transition in medicine: deep learning.

Deep learning offers the ability to personalize care by using data to provide personalized care plans and automate tasks to allow for more face-to-face interaction between patient and caregiver. For the athlete population and practice of sports medicine, digitization and democratization are increasingly emphasized, as they are tied to performance. Activity data have become ubiquitous in most consumer mobile health devices and can be leveraged to empower the sports medicine specialist to guide the delivery of care, from optimizing performance to appropriately timing recovery. As Big Data continue to accumulate from the population of athletes increasingly interested in performance health data, deep learning serves to interpret baseline performance and treatment metrics to guide care beyond the perioperative period, assisting with rehabilitation and return to prior performance to better evaluate the factors related to recovery at the individual and population levels. In the example of anterior cruciate ligament (ACL) reconstruction, return to sport remains a moving target. The timetable may be able to be better defined from continuous data derived and interpreted from metrics outside the orthopaedic and physical therapy appointments, utilizing daily rehabilitation performance and recovery feedback to incrementally adjust the care plan. Presented with these recommendations from the ML algorithm, the physician and patient can collaboratively make decisions regarding progression of activities.

Deep learning will undoubtedly alter the role of the physician who is tasked with receiving a report of a data trend through deep learning processing, rather than interpreting each and every data point made available over an extended period, which risks data desensitization. Therefore, it is vital for orthopaedic surgeons to gain a fundamental appreciation for AI principles to appreciate the paradigm shift it represents, not just in sports medicine, but in the practice of medicine as a whole.

Promise

In his 1955 proposal, McCarthy envisioned AI as "the science and engineering of making intelligent machines."[24]

He predicted that these machines would be capable of performing feats previously thought exclusive to human intelligence, such as abstract thought, advanced problem solving, and iterative self-improvement. In 1976, Jerrold S. Maxmen, a psychiatry professor at Columbia University, predicted that AI would bring about the "post-physician era" by the 21st century,[23] describing the change as "possible, inevitable, and desirable."[22] Although AI has not and likely will not replace the role of physicians, AI is already fundamentally ingrained within many facets of today's society. Some examples of AI include self-driving cars, targeted advertisements, and high-frequency stock trading.[44]

A common concern surrounding AI is the degradation of the patient-physician relationship and the loss of humanism in medicine. After all, if one algorithm is diagnosing an ACL tear from imaging, another is prescribing preoperative physical therapy, and yet another is guiding the patient along the postoperative care pathway, is the physician being replaced by the computer? Most agree that health care should be human facing. However, currently, the average physician spends 15.7 minutes per patient encounter, with patients speaking an average of 5.3 minutes.[43] Meanwhile, that same physician can be expected to spend an average of 5.9 hours a day working in the EHR,[2] with nearly one-half of that time focused on administrative tasks such as documentation, billing and coding, order entry, and inbox management. So, rather than "How will AI remove humanity from health care?" the question becomes "How human was health care to begin with?" As counterintuitive as it may seem, AI can achieve the opposite of what many fear by removing time-intensive administrative burdens.[10] By liberating nonclinical constraints from physicians, physical therapists, and athletic trainers through supportive AI tools that automate redundant tasks from care coordination to routine documentation and orders, more time can be spent with patients augmenting the patient-physician relationship. Additionally, the future applications of AI in the field may take the form of intraoperative software support, such as the increasingly popular robot-assisted surgery in lower extremity arthroplasty, which eliminated the use of cutting guides with arm-controlled saws that do not physically allow for an inaccurate bony resection. Such an evolution can be readily appreciated when drilling tunnels in ACL reconstructions and executing lower extremity realignment osteotomy operations, among other use cases.

Several large-scale factors likely play a role in the recent acceleration of AI implementation in health care.[44] One factor is economic: it is becoming increasingly apparent that health care in the United States is a nonsustainable business model with most costs attributed to administrative burdens, which AI may alleviate with automation.[21,28,31] Similarly, spending on pharmaceuticals with surprisingly low rates of efficacy contributes to this high expenditure.[40] In sports medicine, biologics represent expensive treatment modalities with unknown clinical effectiveness.[39] The powerful pattern recognition capability of AI may help target athletes who are more likely to benefit from biologics, offering exciting potential in improving outcomes and reducing expenditures.

An additional contributing factor is the generation of patient data on an unprecedented scale. From high-resolution medical imaging, continuously evolving EHRs, and numerous diagnostic tests, each patient encounter produces tremendous discrete data points, generating Big Data that cannot be effectively analyzed with human processing or standard statistical methods. One study of EHRs found that a single patient's health record was associated with an average of approximately 32,000 unique data elements.[26] In an era of information overload, a physician is tasked with synthesizing this volume of data and arriving at a clinical decision, a seemingly impossible task given "insufficient time, insufficient context, and insufficient presence."[44] Judicious employment of AI and its predictive abilities may mitigate economic sustainability and overwhelming data.

Limitations

AI carries limitations. ML techniques create a "black box" phenomenon, in which the user can access only the inputs and outputs of an algorithm, not the inner workings.[45] Although a model may be able to make an accurate prediction, we are sometimes unable to know the specific inferences and relationships evaluated by the algorithm. Not knowing why a decision is exactly made spurred the AI Now Institute to recommend in 2017 that "core public agencies, such as those responsible for criminal justice, healthcare, welfare, and education should no longer use black box AI and algorithmic systems."[6] Some believe the black box phenomenon risks the deskilling of physicians and other providers, the displacement of physician jobs, and the devaluation of human experience and clinical intuition. For the practicing sports medicine surgeon, we may be able to produce a suitable algorithm that decides when to use a biologic agents for the treatment of musculoskeletal conditions, though we may never have the specific knowledge guiding this decision in specific patient scenarios. Although an ML algorithm may not be able to delineate why bone marrow aspirate concentrate would be a useful adjunct, having supportive decision making derived from the global body of evidence to recommend which cases would result in increased benefit may be a pragmatic application for tomorrow's sports medicine practice.

There exist ethical considerations relating to data sharing and patient privacy. Beyond navigating deidentified data sharing, another concern is the introduction of contradictory plans when a physician's desired course of action differs from what is recommended by an "expert system" ML tool.[9] Certainly, the ultimate clinical decision starts and ends with the treating physician of record, but this opens up medicolegal concerns when "disagreeing" with an algorithm.[41,48] Similarly, ML may cloud clinical decision making or cause physicians to be wary of deviating from algorithms. However, in the early stages of introducing ML into clinical practice, it will be important to recognize that these support tools carry limitations and by no stretch of the imagination represent the gold standard, especially when such models require iterative feedback and improvement.[32]

AI IN THE SPORTS MEDICINE LITERATURE

In this section, we review the use of AI-based techniques in sports medicine as a prelude for what is to come as it relates to (1) athlete injury prediction, (2) the interpretation of medical imaging, (3) patient-reported outcome measures (PROMs), (4) the delivery of value-based care, and (5) the improvement of the patient experience.

Athlete Injury Prediction

Professional sports are a billion-dollar industry that depends on the maintenance of player health as premium asset commodities. This involves a number of expenses, including dieticians, trainers, physicians, and physical therapists, all with the goal of maximizing player performance and availability. As such, injury prevention is a focal point in optimizing player health. For the 2014-2015 National Basketball Association season, missed games attributed to injury accounted for a loss of $344 million in player salaries.[18] For the 2019-2020 season, the National Football League spent an estimated $521 million on injured players.[12] With the breadth of statistics and player metrics surrounding professional sports, ML may provide a competitive advantage that franchises seek as they search for an ideal tool to aid with injury prevention and prediction.

In 2018, the Cleveland Clinic's Department of Orthopaedic Surgery established the Machine Learning Arthroplasty Laboratory, with the goal of exploring practical implementation of AI techniques in the practice of orthopaedics, specifically in arthroplasty and sports medicine.[3,34,35,37,38] Most recently, this group applied ML techniques to predict next-season injury risk for National Hockey League and Major League Baseball players.[15,20] For hockey players, Karnuta et al[15] compiled yearly injury data as well as player-specific metrics such as age, performance metrics, and injury history. Multiple ML algorithms were trained and compared in performance for predicting next-season injury. This study demonstrated that the best-performing algorithm (XGBoost) predicted next-season injury with an accuracy of 94.6% (SD = 0.5%), outperforming logistic regression and demonstrating good to excellent reliability. For baseball players, data encompassed 1931 position players and 1245 pitchers, including player age, performance, and injury history. Of the 84 algorithms tested, the best-performing algorithm (Top Three Ensemble) demonstrated an accuracy of 70% (SD = 2%) at predicting next-season injury. The model outperformed logistic regression and demonstrated fair reliability. In both studies, ML techniques were superior to logistic regression at predicting future player injury. Further studies may look into obtaining official professional league databases, which contain metrics unavailable to the public as well as more granular injury data that could improve the predictive power of these algorithms.

Outside of professional sports, wearable health technology has become a massively popular industry, with a market size of just over US$13 billion in 2019.[47] The amateur athlete now has access to watches, straps, and bands that can provide numerous health metrics, facilitating a growing demand from the home fitness enthusiast to optimize one's training. This lucrative market for fitness devices may provide the driving force for the further development and application of AI in sports training with the increasing prevalence of such granular data.

Imaging

The powerful pattern recognition capabilities of AI naturally lends itself to the automated interpretation of medical imaging: (1) there are often large databases of preexisting medical imaging that can provide ample training and testing sets; (2) the purpose of image interpretation involves straightforward classification; and (3) images can be processed and standardized before algorithm training, allowing for structured input. Preprogrammed algorithms have demonstrated accurate diagnosis of arthritis on radiographs. Urish and Reznik[46] described the use of medical imaging data in a technique that analyzes pixels in a radiograph image to recognize pertinent structures and specific features to create a pattern. When presented with an unknown image, the algorithm was shown to "decide" if it was consistent with a known model for osteoarthritis. This algorithm could be expanded to predict which patients have more advanced pathology or would benefit most from surgical intervention. With magnetic resonance imaging data, acute cartilage or ligamentous pathology could be immediately detected for triage to a sports specialist.

ML also has utility in detecting knee injury from gait analysis. A random forest computer system developed by Kotti et al[17] takes input body kinetics and produces an output estimate of the likelihood of knee osteoarthritis. Furthermore, it identifies the discriminating parameters and set of rules that led to the decision. This explanation mimics "interpretation" and increases the value of the diagnosis. In the study, locomotion data from 47 participants with osteoarthritis and 47 healthy participants who walked on plates with piezoelectric force sensors included the following parameters: vertical, anteroposterior, and mediolateral ground-reaction forces such as mean value, push-off time, and slope. A similar process could readily be used to assess gait before and after arthroscopic and mini-open procedures to create objective tools that can better evaluate our patients' outcomes.

In a 2020 study, Ramkumar et al[36] applied an ML model to discern, for patients undergoing arthroscopic correction of femoroacetabular impingement syndrome (FAIS), which preoperative radiographic indices from preoperative computed tomography scans of the hip predicted significant changes in 1- and 2-year PROMs. These indices included the modified Harris Hip Score, the Hip Outcome Score–Activities of Daily Living and Sport Specific subscales, as well as the International Hip Outcome Tool–33. Separate random forest models, trained on a database of 1735 patients with FAIS, were created for each of the 4 outcome measures. The study found that no specific radiographic index or combination of indices was predictive of improvement in any of the 4 PROMs at 1- or 2-year follow-up in the setting of strict surgical indications. Figure 2 illustrates a workflow diagram of how the ML algorithm interprets the relationship between radiographic hip indices and PROMs.

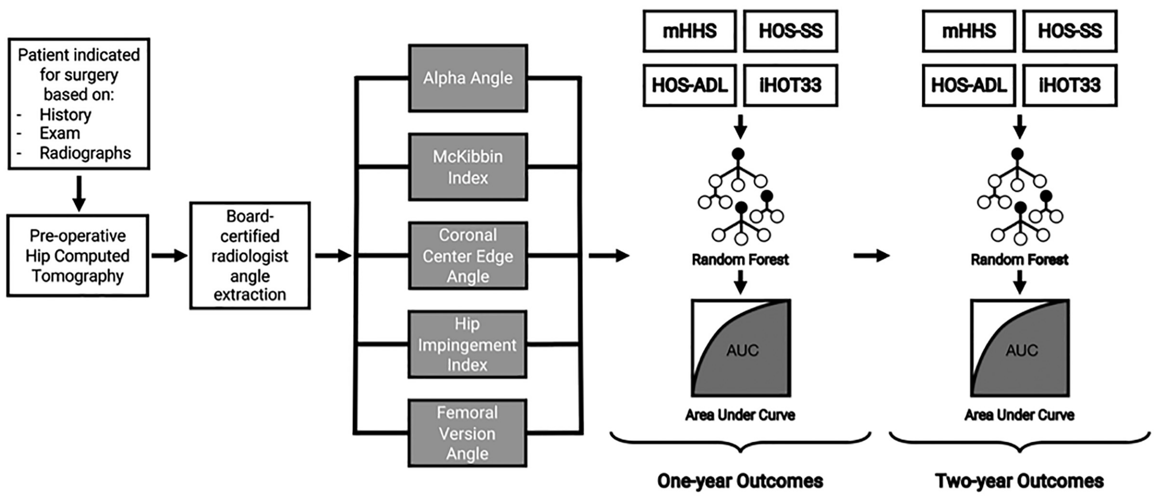

Figure 2. Schematic of the constructed machine learning models assessing for the relationship between critical radiographic indices and patient-reported outcome measures at 1 and 2 years. HOS-ADL, Hip Outcome Score–Activities of Daily Living subscale; HOS-SS, Hip Outcome Score–Sport Specific subscale; iHOT-33, International Hip Outcome Tool–33; mHHS, modified Harris Hip Score.

Patient-Reported Outcome Measures

PROMs have become increasingly valuable quality metrics in determining the success of an intervention. To this end, in a 2020 study Nwachukwu et al[30] investigated the application of ML to predict changes in PROMs after arthroscopic FAIS surgery. An ML model was built using the LASSO algorithm (least absolute shrinkage and selection operator) for feature selection, followed by logistic regression for the selected features. The model, trained on records of 898 patients with femoroacetabular impingement, was able to identify salient predictive variables for achieving clinically meaningful outcomes. Anxiety/depression, symptom duration >2 years, preoperative intra-articular injection, and high preoperative outcome scores were all found to be predictive of inability to achieve a minimal clinically important difference across 3 hip-specific PROMs.[30]

Another example of this capability is a 2019 study by Bloomfield et al[4] that employed ML in the analysis of data obtained from wearable sensors after primary total knee arthroplasty. Using an instrumented timed up-and-go test, the wearable sensor system produced 55 metrics for each patient for analysis. A *k*-means model was created to separate patients into 2 groups by functional outcome, with significantly different test completion times. When the functional recovery of these 2 "clusters" was tracked to their 12-week follow-ups, the study found that 1 cluster had higher PROMs than the other. This ML tool demonstrates clinical utility with early prediction of patients who are most at risk of developing poor postoperative functional outcomes and PROMs. Such an application could be readily applied to other rehabilitation-based tests beyond the timed up-and-go test to assess postoperative recovery after arthroscopic treatments.

Value-Based Metrics

Another relevant application of AI is the promotion of value-conscious care. Deep learning may provide the roadmap for successful navigation in this increasingly restrictive economic climate. One key issue is the current inability to preoperatively communicate value of care rendered to a specific patient for elective surgery. Karnuta et al[16] assessed the capability of artificial neural networks to predict length of stay, discharge disposition, and inpatient charges for primary anatomic, reverse, and hemishoulder arthroplasty. This model predicted inpatient costs with an accuracy ranging from 69% to 77%, as well as discharge disposition and length of stay with fair to good accuracy (72%-75% and 78%-92%, respectively). In the future, ML models may provide physicians with the ability to offer an evidence-based, patient-specific tool that preoperatively communicates value metrics relevant to all stakeholders. These metrics allow physicians to have valuable discourse with patients for expectation management, while also being useful in reimbursement arbitration of preauthorization with payers.

Patient Experience

In the pursuit of patient-centered care, patient experience has grown increasingly important and may be tied to reimbursement.[28] Postencounter surveys often result in nonstandardized data in the form of patient narratives. Additionally, at a large-enough scale of data collection, these surveys are nearly impossible to interpret in a systematic, meaningful manner. In a 2019 study applying natural language processing—an ML technique used to interpret unstructured language—the records of 186 patients who had undergone primary total shoulder arthroplasty at a single institution

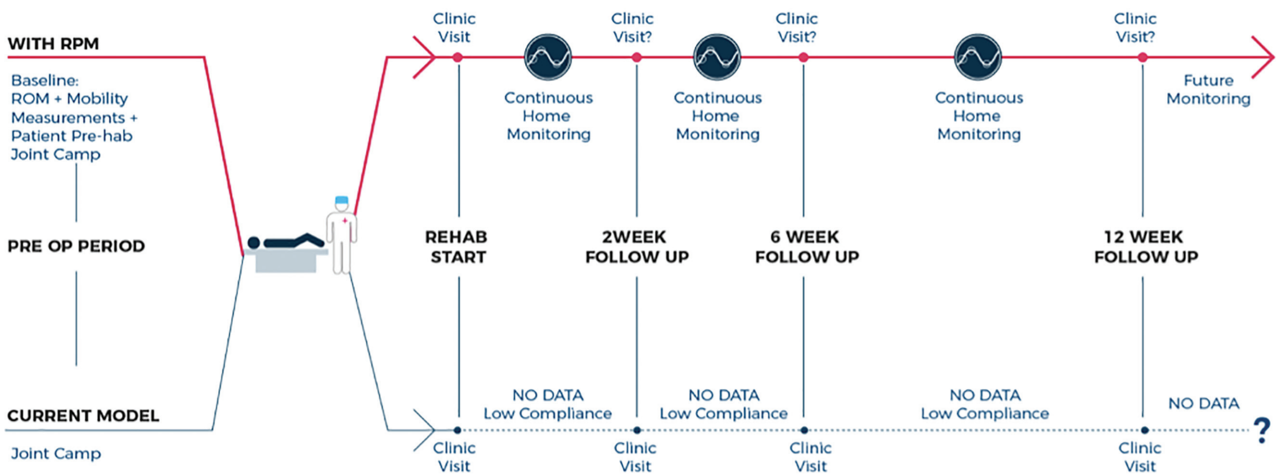

Figure 3. Data stream workflow of the remote patient monitoring system depicts the wearable knee sleeve transmitting motion data to the smartphone, which then transmits these and all other data (steps, patient-reported outcome measures, opioid use) to the dashboard. The data are then analyzed by the machine learning algorithm and instantaneously transmitted back to the patient while being stored on the care team dashboard. This offers the ability to improve perioperative data capture despite remotely caring for our patients. Pre op, preoperatively; ROM, range of motion; RPM, remote patient monitoring.

were analyzed.[25] This sentiment analysis revealed common themes surrounding negative reviews, which often involved room condition (27%), time management (17%), communication (13%), and compassion (12%). Similar sentiment analyses have long been employed extensively in the fields of marketing and advertising, where they serve as powerful tools to assess consumer perception of brands.[33] Such analyses illustrate the ideal implementation of AI in performing a useful function that would otherwise be burdensome and time-intensive, while providing feedback that augments the ability of a physician to work toward improving the environment that affects the patient experience perioperatively.

In the era of the COVID-19 pandemic, the patient experience is increasingly tied to access via remote patient monitoring and telemedicine. One particular system (FocusMotion) implements AI to remotely monitor patients through the use of Bluetooth-enabled braces that communicate objective and subjective data to a mobile application, which are subsequently transmitted to an ML algorithm.[34,35] These data are instantaneously interpreted to highlight warning signs, as stipulated by the surgeon, and display mobility, range of motion, PROMs, opioid consumption, and home exercise plan compliance in a central dashboard shared with the patient and care team; this was found to increase patient engagement and motivation to rehabilitate after knee surgery.[34,35] As seen in Figure 3, this remote patient monitoring system employs AI to paradigmatically shift how we follow patients without sacrificing value-based principles and the patient experience.

CONCLUSION

AI has revolutionized the technology sector and is poised to transform orthopaedics, particularly sports medicine. ML has the capability of automating redundant tasks, allowing physicians to spend more time with patients. The technology should be viewed as a physician aid to augment a physician's capabilities rather than replace one's responsibilities. Additionally, it is important that sports medicine specialists not consider this explosive area of research outside their expected scope of understanding. The future practice of orthopaedic surgery necessitates that surgeons gain sufficient familiarity with AI and ML concepts, seizing the opportunity to leverage this powerful technique and take a participatory role in its responsible deployment.

An online CME course associated with this article is available for 1 *AMA PRA* Category 1 Credit™ at https://www.sportsmed.org/aossmimis/Members/Education/AJSM_Current_Concepts_Store.aspx. In accordance with the standards of the Accreditation Council for Continuing Medical Education (ACCME), it is the policy of The American Orthopaedic Society for Sports Medicine that authors, editors, and planners disclose to the learners all financial relationships during the past 12 months with any commercial interest (A 'commercial interest' is any entity producing, marketing, re-selling, or distributing health care goods or services consumed by, or used on, patients). Any and all disclosures are provided in the online journal CME area which is provided to all participants before they actually take the CME activity. In accordance with AOSSM policy, authors, editors, and planners' participation in this educational activity will be predicated upon timely submission and review of AOSSM disclosure. Noncompliance will result in an author/editor or planner to be stricken from participating in this CME activity.

REFERENCES

1. Adams M, Chen W, Holcdorf D, McCusker MW, Howe PDL, Gaillard F. Computer vs human: deep learning versus perceptual training for

the detection of neck of femur fractures. *J Med Imaging Radiat Oncol*. 2019;63(1):27-32.
2. Arndt BG, Beasley JW, Watkinson MD, et al. Tethered to the EHR: primary care physician workload assessment using EHR event log data and time-motion observations. *Ann Fam Med*. 2017;15(5):419-426.
3. Artificial intelligence and machine learning across the care continuum in lower extremity arthroplasty. Consult QD. Accessed May 14, 2020. https://consultqd.clevelandclinic.org/artificial-intelligence-and-machine-learning-across-the-care-continuum-in-lower-extremity-arthroplasty/
4. Bloomfield RA, Williams HA, Broberg JS, Lanting BA, McIsaac KA, Teeter MG. Machine learning groups patients by early functional improvement likelihood based on wearable sensor instrumented preoperative timed-up-and-go tests. *J Arthroplasty*. 2019;34(10):2267-2271.
5. Cabitza F, Locoro A, Banfi G. Machine learning in orthopedics: a literature review. *Front Bioeng Biotechnol*. 2018;6:75.
6. Campolo A, Sanfilippo M, Whittaker M, Crawford K. *AI Now 2017 Report*. AI Now Institute; 2017.
7. Esteva A, Robicquet A, Ramsundar B, et al. A guide to deep learning in healthcare. *Nat Med*. 2019;25(1):24-29.
8. Gan K, Xu D, Lin Y, et al. Artificial intelligence detection of distal radius fractures: a comparison between the convolutional neural network and professional assessments. *Acta Orthop*. 2019;90(4):394-400.
9. Grote T, Berens P. On the ethics of algorithmic decision-making in healthcare. *J Med Ethics*. 2020;46(3):205-211.
10. Haeberle HS, Helm JM, Navarro SM, et al. Artificial intelligence and machine learning in lower extremity arthroplasty: a review. *J Arthroplasty*. 2019;34(10):2201-2203.
11. Helm JM, Swiergosz AM, Haeberle HS, et al. Machine learning and artificial intelligence: definitions, applications, and future directions. *Curr Rev Musculoskelet Med*. 2020;13:69-76.
12. Injuries cost NFL teams over $500 million in 2019. Hospital for Special Surgery. Accessed June 28, 2020. https://news.hss.edu/injuries-cost-nfl-teams-over-500-million-in-2019/
13. Kang YJ, Yoo JI, Cha YH, Park CH, Kim JT. Machine learning–based identification of hip arthroplasty designs. *J Orthop Transl*. 2020; 21:13-17.
14. Karhade AV, Schwab JH, Bedair HS. Development of machine learning algorithms for prediction of sustained postoperative opioid prescriptions after total hip arthroplasty. *J Arthroplasty*. 2019;34(10): 2272-2277.
15. Karnuta J, Luu B, Haeberle H, et al. Machine learning outperforms regression analysis to predict next season MLB player injury: epidemiology and validation of 13,982 player-years from performance and injury profile trends between 2000-17. *Orthop J Sports Med*. 2020;8(11):2325967120963046.
16. Karnuta JM, Churchill JL, Haeberle HS, 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(11):2385-2394.
17. Kotti M, Duffell LD, Faisal AA, McGregor AH. Detecting knee osteoarthritis and its discriminating parameters using random forests. *Med Eng Phys*. 2017;43:19-29.
18. Lewis M. It's a hard-knock life: game load, fatigue, and injury risk in the National Basketball Association. *J Athl Train*. 2018;53(5):503-509.
19. Lindsey R, Daluiski A, Chopra S, et al. Deep neural network improves fracture detection by clinicians. *Proc Natl Acad Sci U S A*. 2018;115(45):11591-11596.
20. Luu B, Wright A, Haeberle H, et al. Machine learning outperforms logistic regression analysis to predict next season NHL player injury: an analysis of 2,322 players from 2007-2017. *Orthop J Sports Med*. 2020;8(9):2325967120953404.
21. Macdorman MF, Declercq E, Cabral H, Morton C. Recent increases in the US maternal mortality rate: disentangling trends from measurement issues. *Obstet Gynecol*. 2016;128(3):447-455.
22. Maxmen JS. Long-term trends in health care: the post-physician era reconsidered. In: Schwefel D, ed. *Indicators and Trends in Health and Health Care*. Springer; 1987:109-115.
23. Maxmen JS. *The Post-physician Era: Medicine in the Twenty-first Century*. Wiley; 1976.
24. McCarthy J, Minsky ML, Rochester N, Shannon CE. A proposal for the Dartmouth summer research project on artificial intelligence. *AI Mag*. 1955;27(4):12-14.
25. Menendez ME, Shaker J, Lawler SM, Ring D, Jawa A. Negative patient-experience comments after total shoulder arthroplasty. *J Bone Joint Surg Am*. 2019;101(4):330-337.
26. Milinovich A, Kattan MW. Extracting and utilizing electronic health data from Epic for research. *Ann Transl Med*. 2018;6(3):5.
27. Mintz Y, Brodie R. Introduction to artificial intelligence in medicine. *Minim Invasive Ther Allied Technol*. 2019;28(2):73-81.
28. Myers TG, Ramkumar PN, Ricciardi BF, Urish KL, Kipper J, Ketonis C. Artificial intelligence and orthopaedics. *J Bone Joint Surg Am*. 2020;102(9):830-840.
29. Navarro SM, Wang EY, Haeberle HS, et al. Machine learning and primary total knee arthroplasty: patient forecasting for a patient-specific payment model. *J Arthroplasty*. 2018;33(12):3617-3623.
30. Nwachukwu BU, Beck EC, Lee EK, et al. Application of machine learning for predicting clinically meaningful outcome after arthroscopic femoroacetabular impingement surgery. *Am J Sports Med*. 2020;48(2):415-423.
31. Papanicolas I, Woskie LR, Jha AK. Health care spending in the United States and other high-income countries. *JAMA*. 2018;319(10):1024-1039.
32. Podgorelec V, Kokol P, Stiglic B, Rozman I. Decision trees: an overview and their use in medicine. *J Med Syst*. 2002;26(5):445-463.
33. Puschmann C, Powell A. Turning words into consumer preferences: how sentiment analysis is framed in research and the news media. *Soc Media Soc*. 2018;4(3):205630511879772.
34. Ramkumar PN, Haeberle HS, Bloomfield MR, et al. Artificial intelligence and arthroplasty at a single institution: real-world applications of machine learning to big data, value-based care, mobile health, and remote patient monitoring. *J Arthroplasty*. 2019;34(10):2204-2209.
35. Ramkumar PN, Haeberle HS, Ramanathan D, 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(10):2253-2259.
36. Ramkumar PN, Karnuta JM, Haeberle HS, et al. Radiographic indices are not predictive of clinical outcome among 1,735 patients indicated for hip arthroscopy: a machine learning analysis. *Am J Sports Med*. 2020;48(12):2910-2918.
37. Ramkumar PN, Karnuta JM, Navarro SM, et al. Deep learning preoperatively predicts value metrics for primary total knee arthroplasty: development and validation of an artificial neural network model. *J Arthroplasty*. 2019;34(10):2220-2227.e1.
38. Ramkumar PN, Navarro SM, Haeberle HS, 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(4):632-637.
39. Rodeo SA. Biologic approaches in sports medicine: potential, perils, and paths forward. *Am J Sports Med*. 2016;44(7):1657-1659.
40. Schork NJ. Personalized medicine: time for one-person trials. *Nature*. 2015;520(7549):609-611.
41. Semigran HL, Linder JA, Gidengil C, Mehrotra A. Evaluation of symptom checkers for self diagnosis and triage: audit study. *BMJ*. 2015;351:H3480.
42. Sovacool BK. Early modes of transport in the United States: lessons for modern energy policymakers. *Policy Soc*. 2009;27(4):411-427.
43. Tai-Seale M, McGuire TG, Zhang W. Time allocation in primary care office visits. *Health Serv Res*. 2007;42(5):1871-1894.
44. Towards Data Science. The ''black box'' metaphor in machine learning. Accessed June 28, 2020. https://towardsdatascience.com/the-black-box-metaphor-in-machine-learning-4e57a3a1d2b0
45. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. *Nat Med*. 2019;25(1):44-56.
46. Urish K, Reznik A. How would a computer diagnose arthritis on a radiograph? *AAOS Now*. 2018:32-33. https://assets.ct-ortho.com/wp-content/uploads/2019/10/16215008/Dec-2018-AI.pdf

47. Wearable medical device market size, industry report, 2027. Grand View Research. Published 2020. Accessed November 7, 2020. https://www.grandviewresearch.com/industry-analysis/wearable-medical-devices-market
48. Wyatt JC. Fifty million people use computerised self triage. *BMJ*. 2015;351:H3727.
49. Wyles CC, Tibbo ME, Fu S, et al. Use of natural language processing algorithms to identify common data elements in operative notes for total hip arthroplasty. *J Bone Joint Surg Am*. 2019;101(21):1931-1938.
50. Zhang J, Dushaj K, Rasquinha VJ, Scuderi GR, Hepinstall MS. Monitoring surgical incision sites in orthopedic patients using an online physician-patient messaging platform. *J Arthroplasty*. 2019;34(9):1897-1900.