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Artificial Intelligence and Machine Learning

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

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ABSTRACT

Background: Driven by the recent ubiquity of big data and computing power, we established the Machine Learning Arthroplasty Laboratory (MLAL) to examine and apply artificial intelligence (AI) to musculoskeletal medicine.
Methods: In this review, we discuss the 2 core objectives of the MLAL as they relate to the practice and progress of orthopedic surgery: (1) patient-specific, value-based care and (2) human movement.
Results: We developed and validated several machine learning-based models for primary lower extremity arthroplasty that preoperatively predict patient-specific, risk-adjusted value metrics, including cost, length of stay, and discharge disposition, to provide improved expectation management, preoperative planning, and potential financial arbitration. Additionally, we leveraged passive, ubiquitous mobile technologies to build a small data registry of human movement surrounding TKA that permits remote patient monitoring to evaluate therapy compliance, outcomes, opioid intake, mobility, and joint range of motion.
Conclusion: The rapid rate with which we in arthroplasty are acquiring and storing continuous data, whether passively or actively, demands an advanced processing approach: AI. By carefully studying AI techniques with the MLAL, we have applied this evolving technique as a first step that may directly improve patient outcomes and practice of orthopedics.

The theory behind artificial intelligence (AI) has become a reality with the ubiquity of cloud storage and fast computer processors and a commitment to aggregating big data. In orthopedics, the success of a procedure can be defined not by the anatomic restoration on X-ray or the improved motion of a joint, but also by the subjective nature of how the patient—not the surgeon—feels after the procedure. This has led to a paradigmatic shift in orthopedic practice and led to a systematic effort to collect patient-reported outcome data. After the use of countless outcome scores and multiple registries over the past 2 decades of arthroplasty research, we can finally ask the question: what do we do with all of this aggregated data?

Machine learning encompasses computers that can be trained to assist humans with little to no human continuous effort. As Eric Topol [1] penned, high-performance medicine demands "the convergence of human and artificial intelligence" [1]. On one hand, the expenditures exceed outcomes in a flawed United States healthcare business model whereby marginal capital yields diminishing returns. On the contrary, an unimaginable volume of data, or "big data," is being generated from biosensors, imaging storage, electronic medical records, and genome sequencing, such that careful analysis is required to make this information useful, mandating a machine-based approach or algorithm. At our institution, we have made a concerted commitment to outcome-based

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care with the OrthoMiDaS Episode of Care ("OME"), which collects treatment documentation from providers and patients at the beginning and end of a given elective surgical episode of care, to determine if surgery has met expectations [2,3].

The Machine Learning Arthroplasty Laboratory

In recognition of the rapid rise of big data and the ubiquity of powerful machines capable of "learning," in 2018 we established the Machine Learning Arthroplasty Laboratory (MLAL). It is our view that computer-based algorithms represent the primary sustainable way for the future that orthopedic surgeons who desire to make sense of, and take advantage of, all available data to yield the best possible outcomes for patients and the healthcare system. The MLAL was established to create machine-learning algorithms that would explore 2 core objectives directly related to the practice and progress of orthopedic surgery: (1) patient-specific, value-based care and (2) human movement. Orthopedic care and the MLAL operate on 2 fundamental planes: system-based and practice-based. At the system level, outcomes and costs are the 2 primary determinants for value-based care. However, what is viewed as high in value by some patients may not hold true for other individuals. This is evident when comparing patients who desire to run a marathon after their total hip arthroplasty (THA) vs those who simply want to make it to the grocery store. Thus, "value" in medicine is patient-specific, and machine learning offers the ability to account for these patient-level factors and deliver a customized or individualistic approach to value-based care. Although the business of medicine is important for survivorship of our industry, the art of practicing medicine rests on taking into account patient-level preferences. With respect to the MLAL's practice-based goals, we seek to find and apply machine-learning solutions that improve upon the routine orthopedic practice of medicine by prioritizing the patient, assisting the physician, and benefitting relevant stakeholders (eg, hospitals, institutions, and payers).

Patient-Specific and Value-Based Care in the World of Arthroplasty

The early focus of the MLAL on value-based care has followed the legislation and conversation surrounding alternative payment models. In lower extremity joint arthroplasty, the Comprehensive Care for Joint Replacement model aims to apply bundled payments and quality measures to incentivize high quality, coordinated care at a reduced cost. The value-based program has led to early success for programs participating in the Bundled Payments for Care Improvement in total joint arthroplasty. By aligning surgical and administrative staff to reduce clinical and financial variations at one high-volume orthopedic hospital, length of stay (LOS) decreased from 3.4 to 2.7 days, catheter-associated urinary tract infections decreased to 0%, and 30-day readmissions decreased from 5% to 1.6% [4]. Moreover, $522,389 was saved over 271 patients, resulting in gain sharing of $159,571 to the Centers for Medicare and Medicaid Services (CMS) and $362,818 to the hospital. Although preliminary successes have been promising for controlling modifiable systemic risk factors related to inefficient care delivery, "bundling care" as a definitive solution does not address patient-level risk factors.

Bundled payment literature surrounding primary total knee arthroplasty (TKA) and THA demonstrates that patient comorbidities increase perioperative complications and worse outcomes harbored solely by surgeons and hospitals, as insurers reimburse a flat rate [5,6]. Even with some of the most reproducible procedures reimbursed by Medicare, a flat fee for all primary joint arthroplasty patients regardless of patient differences may not be a tenable alternative payment model as the "one size fits all" approach does not account for patient-specific risk. Furthermore, this engenders a volume-based practice whereby healthier, lower risk patients are preferentially selected. This presents a unique ethical challenge for the orthopedic surgeon incentivized, and potentially pressured, to "cherry pick" young, healthy patients and "lemon drop" older patients with comorbidities [7]. To address this problem, and perhaps provide guidance on how best to stratify and appropriately reward or compensate care, we endeavored to create a model that would predict which patients will require additional resources, allowing for preoperative negotiation and risk sharing between payers and providers.

As such, we created and validated a Naïve Bayesian classifier algorithm on a statewide administrative database of approximately 260,000 primary THA and TKA patients to determine the feasibility of predicting LOS and inpatient payments [5,6]. Representing a rudimentary form of machine learning, the Naïve Bayesian classifier is able to study a large dataset, analyze patterns based on the outcome variable of interest (ie, cost and LOS), and predict what predetermined "bucket" to classify a new patient outside the studied dataset would likely resemble (ie, <$12,000, $12,000-24,000, >$24,000 or <3 nights, 3-5 nights, or >5 nights) based on patterns from the previously imbibed dataset. After stratifying these elective patients by their level of preoperative medical complexity using validated anesthesia scoring, we determined the algorithm's error in predicting cost of resources for each stratum. Stated simply, the algorithm uncertainty or "error" represents the risk assumed by the treating surgeon and hospital in the business model of a primary elective lower extremity arthroplasty. For primary TKA patients, reimbursement tiers warrant increases of 3%, 10%, and 15% for moderate, major, and extreme comorbidities; for primary THA patients, reimbursement tiers warrant increases of 3%, 12%, and 32% for moderate, major, and extreme comorbidities [6,7]. These preliminary studies validate the role of machine learning in creating a tiered, patient-specific payment model for Medicare's most commonly reimbursed procedures in THA and TKA [6,7]. However, the limitation of this model centered on the use of only a single database population, creating homogeneity bias, and the inability of a Naïve Bayesian model to output a specific value rather than an LOS or cost "bucket."

Similarly, high-risk patients with hip and femur fractures managed with THA, hemiarthroplasty, or open reduction and internal fixation are equally subject to perioperative complications and worse outcomes. Although the initiative to bundle care for hip and femur fractures has most recently been aborted by the CMS, these nonelective procedures would almost certainly result in financial losses for all institutions treating these patients, building barriers to care where patients are transferred to higher level acuity centers that can endure the financial burden. Since little to no evidence has been presented discussing the viability of such a model, particularly to policymakers and administrators, we similarly applied a Naïve Bayesian model to determine algorithm accuracy in predicting sustainability of a patient-specific payment model using algorithm error [8]. The validated algorithm resulted in an unsustainable, tiered payment model that increased by 46% for major comorbidities and 138% for extreme comorbidities. Our findings demonstrate that the patient's preoperative medical comorbidities greatly contribute to differential costs based on the expected payments in an equitable patient-specific payment model.

Although the focus of our early value-based work has been on payment models, the recently published approaches involve simple Naïve Bayesian approaches, which fall under the category of "supervised learning." With this process, more human involvement is required than "unsupervised learning," as with deep learning architectures like the artificial neural network (ANN). Such ANNs offer the opportunity to improve algorithm accuracy, imbibe external data in multiple formats, and require less effort from humans. As an example, ANNs represent a subtype of machine learning that could process a database full of radiographs labeled with implant designs, attempt to identify a correlation between the radiograph patterns and associated label, and then subsequently identify the implant from a new radiograph if the implant has been previously “learned.” In essence, these ANNs represent a microcosm of experience-based learning and are even schematically organized after the human brain with several processing “nodes” densely connected in an axonal fashion. Like a neuron, one node may receive data from several other “dendritic” nodes but transmit data forward in a unidirectional fashion. In order for a node to “fire” or send data, the weight of the incoming variable must be high enough to stimulate subsequent nodes and establish a correlational relationship. When an ANN is being trained, all weights and thresholds are initially set to random values. Training data are fed to the bottom layer, or the input layer, and it passes through the succeeding layers, getting multiplied and added together in complex ways, until it finally arrives, radically transformed, at the output layer. During training, the weights and thresholds are continually adjusted until training data with the same labels consistently yield similar outputs [9]. As such, the resulting algorithm allows for interconnected relationships between inputs at various levels, with an increasing complexity of the model based on the number of inputs. ANNs may be utilized to process a variety of inputs (ie, patient age, gender, comorbidities) into a single output prediction (ie, hospital charges), based on the predicted tier that the patient would fall into.

Specifically, the MLAL has developed ANNs modeling economic outcomes (LOS, charges) following lower extremity arthroplasty, utilizing deep learning techniques [10,11]. Using a cohort of 175,042 primary TKA patients with 15 preoperative input variables, the ANN predicted LOS, charges, and discharge disposition with a discriminatory power of 74.8%, 82.8%, and 76.1%, respectively, based on the area under the curve [10]. This model demonstrated increased reimbursements by 2.0%, 21.8%, and 82.6% for moderate, major, and severe comorbidities, respectively. Similarly, an ANN developed for primary THA demonstrated area under the curves of 82.0%, 83.4%, and 79.4% for LOS, charges, and disposition, respectively, with charges increasing by 2.5%, 8.9%, and 17.3% for moderate, major, and severe comorbidities, respectively [11]. As additional data are collected in the future, these ANNs are capable of further learning and adjustments in order to improve future predictive capabilities.

Future studies will use multiple databases across the globe for internal and external validation and algorithm refinement, particularly in the ability to more closely predict outcome variables. Presently, stratifying patients into “buckets” remains suboptimal as this increases the risk of oversimplifying patient complexity. However, this represents a first intermediate step to move beyond the “one size fits all” bundled payment. As we acquire finer data, algorithms will be able to predict outcomes with finer accuracy. Other applications of deep learning in orthopedics may include data from the electronic medical record, smartphone, or geography to preoperatively identify patients at risk for readmissions or periprosthetic joint infections prior to the primary procedure.

Mobile Health and Remote Patient Monitoring

Machine learning models may be used to process any large dataset. Beyond the large outcome datasets in registries, our mobile devices are collecting and storing vast quantities of “small data” that too warrants study for clinically meaningful insight. Mobile devices such as smartphones and wearables have become ubiquitous. More than instant connectivity offered cellular networks and the Internet either in your pocket or on your wrist, these devices also represent sensors capable of storing tremendous amounts of personal health data (“mHealth”). The wearables market has grown tremendously since the announcement of the Jawbone Up in 2011 and the subsequent release of the Fitbit Flex in 2013 [12,13]. This relatively new market is expected to be worth $34 billion by 2020 and remains a relatively underutilized tool in healthcare [14]. Although 1 in 6 Americans uses a wearable device and 77% of Americans own a smartphone, the healthcare system has failed to meaningfully integrate any of these technologies into clinical practice that redress workflow, significantly improve care, or decrease costs [15]. Using mHealth, sensors incorporate many different tracking modalities including accelerometers, global positioning system, oximeters, electrocardiograms, gyroscopes, and environmental sensors that are currently being used by consumers to track general physical activity, sleep, posture, and locomotion (number of steps, speed, and distance traveled). However, a limitation of the current mHealth landscape is the fragmentation and lack of interconnectivity between the myriad of available apps. Moreover, skepticism over the accuracy of wearables remains. Recently, smartphone-based technologies have been found to be accurate within 7° and 5° of goniometer measurements for shoulder and knee range of motion, respectively [16,17]. The fundamental strength in mHealth relies on data, but the current state of mobile apps has been limited by the closed nature of proprietary data format, management, and analysis tools that isolate each app. In other words, all the passive data collected by these devices are stored in heterogeneous formats dictated by the various proprietary developers with little to no consideration of aggregating all available data to yield the greatest insights. Herein lies the strength of the “open” mHealth architecture, which offers universal data standards and a global interconnected network [16]. Only once apps are constructed to be “open” can the volume of data be coherent, scaled, and meaningful. Certainly, as with all electronic medical records that rely on remote servers, maintaining Health Insurance Portability and Accountability Act compliance with standard regulatory oversight must be ensured prior to clinical adoption.

Once the “small data” of a given individual’s minute-by-minute step count or heart rate are successfully aggregated into big data, how then do we analyze and make meaning of this continuous data stream? Machine learning once again becomes essential in understanding mHealth, which is where the MLAL is critical. Moreover, to foster bilateral engagement from patient and physician, the user interface must be effortless and utilize real-time feedback. For this reason, the MLAL has partnered with a proprietary data-driven orthopedic solutions developer (FocusMotion, Santa Monica, CA) to create a remote patient monitoring (RPM) system that leverages the power of mHealth data using open architecture, uses AI algorithms to “learn” human movements, and provides real-time feedback. In order for the system to “learn” a movement, an activity is labeled (ie, “straight leg raise”) and subsequently performed while operating the wearable and all positional signals from the sensors are analyzed and “taught” that a particular movement refers to this action. With enough permutations and repetitions of a particular activity, the algorithm begins to recognize and provide feedback regarding an activity. Unlike other platforms, this RPM system is freely available, compatible with any consumer mobile device, and broadly scalable. Although the RPM platform is able to study and provide quantitative feedback on any human body movement, from yoga poses to baseball pitching, we have focused on applying this technology to the primary arthroplasty setting [18].

Presently, measurement after TKA has traditionally been accomplished through clinician in-office assessments, validated

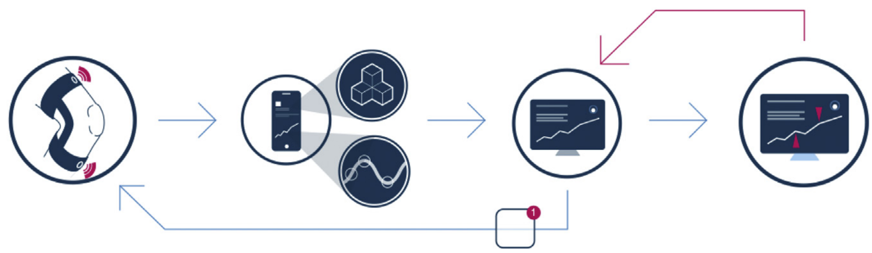

Fig. 1. Schematic of the remote patient monitoring platform. First, the knee sleeve transmits basic spatial data to the smartphone during a standard postoperative rehabilitation TKA exercise. Then, the smartphone transmits this data through the artificial intelligence processor that analyzes the data and immediately returns real-time feedback to the patient regarding number of repetitions, max flexion, or if lacking extension. If the patient does not reach 90° of flexion by 2 weeks postoperatively, the surgeon is notified.

surveys, or both. Both of these assessments have inherent limitations related to subjectivity, objectivity, cost-effectiveness, and time. With the understanding that patients are demanding increased perioperative support and hospitals are pushed to provide higher quality at a lower cost, we have designed a tailored RPM platform for the TKA patient that enables data capture of the following: home exercise plan compliance, daily step count (ie, activity level), daily knee range of motion, weekly patient-reported outcome scores, and opioid use. By providing a knee sleeve that pairs to the patient's smartphone (Fig. 1), we prospectively studied

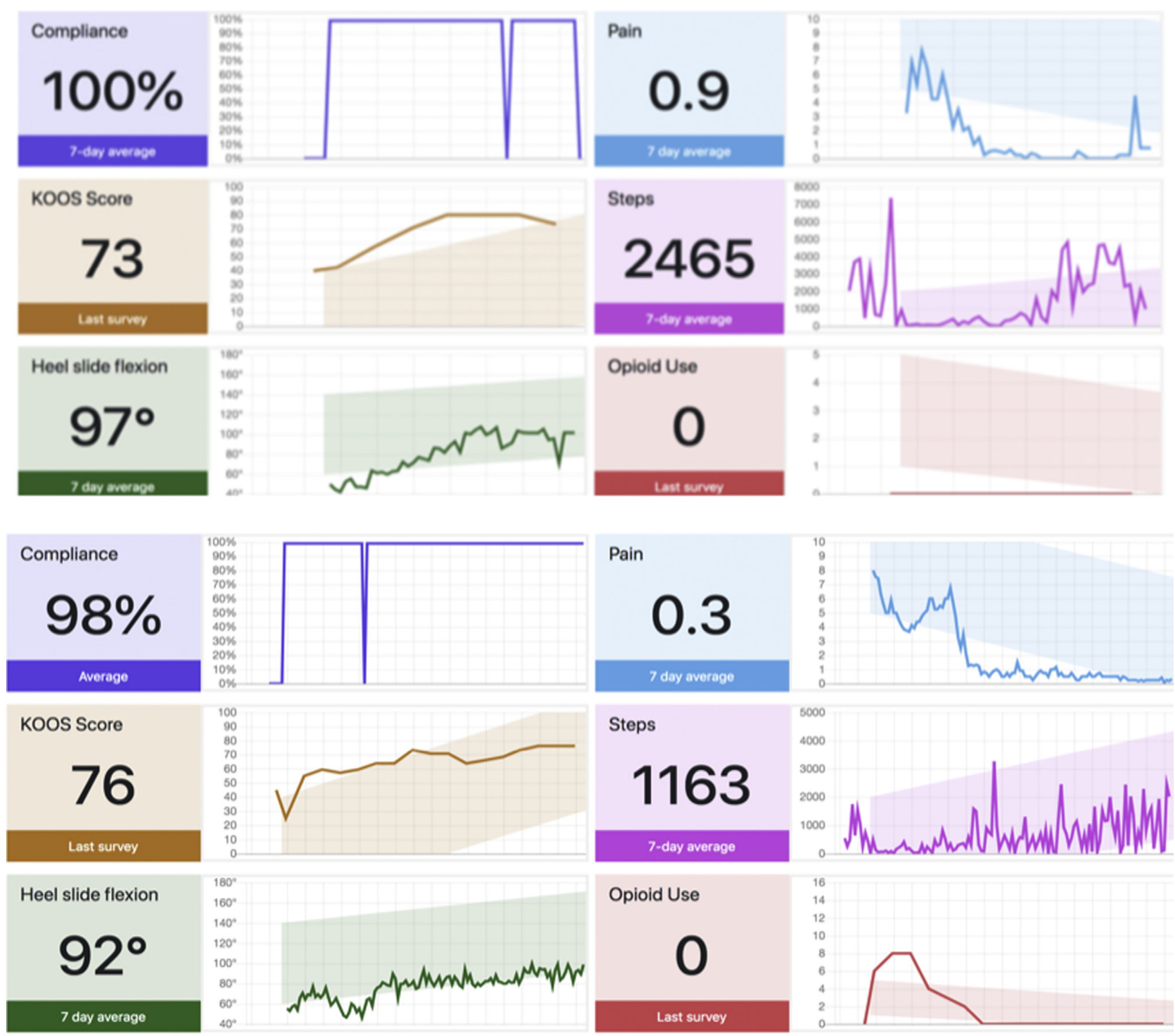

Fig. 2. Summative dashboard data of 2 patients recovering from TKA who both found the remote patient monitoring platform "highly motivating." The trend of their rehabilitation compliance and improving outcome scores (ie, knee injury and osteoarthritis outcome score, self-reported), knee flexion, pain (self-reported), activity (ie, step count), and opioid independency (self-reported) are depicted.

25 primary TKA patients. Prior to study initiation, we recorded the difference in knee flexion between the app and a goniometer measurement by a single clinician across 10 different knees for 5 arbitrary angles each (range 5°-135°), which revealed a mean difference of 7.2° found to be statistically equivocal ($P = .41$). Upon study completion at 90 days postoperatively, not a single patient had uninterrupted data collection, demonstrating excellent connectivity [19]. Moreover, all 22 of the 25 patients available for follow-up interviews found the system motivating and engaging. Daily home exercise program compliance with automated notification reminders pushed to the patient was 62% within the first 90 days postoperatively. Data from 2 patients are presented (Fig. 2). This platform is one of several mobile applications being used worldwide to perioperatively assess and communicate with TKA patients [9,17,20]. Opioid use typically stopped by postoperative day 5, and mean mobility returned to baseline at 6 weeks. This study addresses a critical barrier in the capture of outcome and therapy compliance data that have been previously limited by patient access, discontinuous data, high overhead cost, and capable technology.

From the patient perspective, we have found the RPM platform to engender engagement with their recovery by gamifying the rehabilitation experience with real-time feedback with a live avatar, a dashboard that is both clinician facing and patient facing, and push notifications reminding the patient to perform exercises and complete surveys. Aside from potentially decompressing redundant pre-paid clinic visits in the global period for the surgeon or physician assistant, there is no change to the workflow or additional burden of expectation aside from a notification that a patient has not reached 90° of flexion at a predetermined post-operative time point. Additionally, CMS may permit durable medical equipment and RPM billing for this system. Hospitals stand to gain savings in decreased outpatient therapy expenditures, allowing for more profit from the flat bundled payment, as well as potential decreases in outcome tracking expenditures. To administrators and policy makers, this RPM platform provides the objective parametric data needed in an increasingly value-based care model. Specifically, knowledge of the preoperative state in terms of function, pain, and limitations in activities of daily living may be postoperatively compared to determine the “value” of the TKA. Conversely, this technology offers surgeons the opportunity to identify potential causes for unfavorable outcomes by capturing therapy noncompliance despite a thorough discussion of expectation management and well-executed surgical plan. These benefits are realized with little to no overhead or administrative cost given the ubiquity of mobile devices and Internet connectivity.

Although the MLAL is using the technology for immediate clinical application at our institution, the 18,000 data points gathered from a single set of patient exercises offers a valuable small data repository of human movement that may be used for further investigational biomechanics studies. One of the greatest implications of this research is characterization of the “normal” post-operative trajectory using continuous data points that can be used for benchmarking. As more individualized “small data” are aggregated from patients, population-level commonalities and differences may be analyzed for contributing factors (ie, socioeconomic status, gender, age, and comorbidities) to guide expectation management, shared decision-making, optimization of any modifiable risk factors, and future policy.

Conclusion

Not too long ago, big business was a foreign concept to physicians. Today, many are well versed in the practice and have been forced to self-teach fundamental business principles to adapt to the changing times of an increasingly value-based care model. Tomorrow’s next challenge for the field of medicine, and particularly value-centered orthopedics, is utilizing big data. The rapid rate with which we are acquiring and storing continuous data, whether passively or actively, demands an advanced processing approach: machine learning. Although machine learning remains a subset of AI, the dissociation between man and the machine is a concept we must begin to embrace as a profession and subsequently harness to our benefit. By carefully studying machine learning techniques (ie, MLAL) and adapting them into our clinical workflow and systemic infrastructure, we may be successful in achieving “high performance medicine.” For orthopedics, and high volume subspecialties like arthroplasty in particular, this means remaining at the forefront in knowledge of the strengths and limitations of these evolving technologies that most certainly will directly impact our field. Permitting automation should not necessarily raise suspicion, as certain time-consuming processes (ie, “clicks” in the electronic medical record) may indeed warrant automation. On the other hand, as physicians we must learn to recognize how these algorithms can be applied to calculate previously immeasurable metrics, from preoperative patient risk to rehabilitation compliance, and offer great room for innovation that may translate into improved patient care, reduced surgeon burnout, and controlled resource costs.

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