The role of artificial intelligence in orthopaedic surgery

ABSTRACT

Despite significant advances in orthopaedic surgery, variability still exists between providers and practice locations, and process inefficiencies are found throughout the health care continuum. Evolving technologies, namely artificial intelligence, challenge the status quo by improving patient care in four areas: diagnosis, management, research and systems analysis. Artificial intelligence shows promise in promoting practice efficiency, personalizing patient care, improving institutional research capacity, and expanding high quality orthopaedic care to lower resource settings. Physicians should be involved in the development of artificial intelligence algorithms to ensure that patients derive maximum benefit from new advances while considering the ethical challenges of implementation.

Orthopaedic surgery has evolved beyond recognition from its inception as a battlefield specialty described by Nicolas Andry almost 300 years ago. Enhanced surgical technique, better understanding of disease pathogenesis, restructuring of services and formal surgical training all mean that outcomes in fields as varied as orthopaedic tumour, trauma and spinal surgery are now vastly improved.

However, despite these advances, a successful outcome is not guaranteed. In the case of total hip replacement – described in the Lancet as the operation of the century – 4% of patients do not experience an improvement following surgery (Learmonth et al, 2007). Furthermore, outcomes are not uniform. The likelihood of success differs significantly between patients and hospitals (Mahomed et al, 2003; Cram et al, 2007). Improving the likelihood of success is the goal of any physician and institution. In part, this can be achieved by pushing the boundaries of current knowledge through innovation. However, this is also achieved by 'ironing out the creases': ensuring that all surgeons and institutions can mimic the positive outliers – those that have the best outcomes.

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A number of approaches can be used to help surgeons and institutions mimic positive outliers (Gawande, 2004). Databases such as the UK's and Australia's National Joint Registries and the National Trauma Data Bank in the United States serve to improve our incomplete knowledge and also ensure the free flow of information between surgeons and institutions. Guidelines from organizations like the UK's National Institute for Health and Care Excellence, and protocols such as Advanced Trauma Life Support, are designed to ensure that surgeons treat patients in accordance with best evidence. Programmes such as the UK's Getting It Right First Time can encourage providers to rethink how they deliver care, for example, ensuring patients with complex orthopaedic conditions are seen by surgeons and institutions with appropriate expertise (Cole et al, 2016; Getting It Right First Time, 2018).

However, despite the proliferation of guidelines, databases and robust research, variability in practice persists: consult a surgeon in the UK and your chances of undergoing a shoulder arthroplasty are six times lower than if you are seen in Germany (Lübbeke et al, 2017). Seek the advice of a spinal surgeon in early practice and you are more likely to be offered a fusion than if you are seen by a more senior surgeon (Schallmo et al, 2017). Undergo primary joint arthroplasty in a centre performing fewer than 100 procedures annually and your operation is likely to cost more, and you are also more likely to experience a complication (Courtney et al, 2018).

This non-uniformity of care reflects the fact that medicine is evolving at an exponential rate and becoming increasingly complex, to the extent that the tools we currently have can no longer cope with the pace of change and the volume of information available. For example, the National Institute for Health and Care Excellence published guidance covering the use of cement augmentation to treat vertebral compression fractures in April 2013. Within 1 month, further randomized controlled data were published that may have influenced the guidelines (Van Meirhaeghe et al, 2013). Thus, one could argue that the guidelines were outdated soon after their release. As such, it is increasingly difficult to offer contemporaneous gold standard care in a coordinated manner.

Artificial intelligence offers a solution by both pushing the boundaries of current knowledge and by improving

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the transfer of information, systems and processes. Artificial intelligence has already been studied in specialities as diverse as radiology (Jha and Topol, 2016), oncology (Ehteshami Bejnordi et al, 2017), primary care (Baum et al, 2017) and basic sciences (Ching et al, 2018). Despite this, artificial intelligence is beyond the scope of curriculum at most medical schools, and many physicians are unaware of the potential of and the challenges posed by artificial intelligence.

Orthopaedic surgery is amenable to transformation by artificial intelligence for the following reasons:

1. It consists of well-described processes with national infrastructures of primary, secondary and tertiary care
2. It is a rapidly changing speciality with continually evolving implants and techniques
3. It is a growth speciality, attributed to the demand from an aging population
4. It is a speciality that operates in a cost-conscious environment
5. Initiatives to systematically collect outcomes data already exist at the national and international level, and these can be used to develop artificial intelligence algorithms.

This article serves as a primer for physicians in defining artificial intelligence, describing how artificial intelligence may impact medicine, with orthopaedic surgery as an example, and outlining why physicians need to play a central role in the development of new applications.

Artificial intelligence: a definition

Artificial intelligence aims to replicate human intelligence using computers. Artificial intelligence can be divided into artificial general intelligence, also called broad artificial intelligence, and narrow artificial intelligence – artificial intelligence focused on a single task such as image recognition or speech translation. Presently, all artificial intelligence is narrow artificial intelligence and consists of a technique known as machine learning – where software is created to find associations of predictive power in data. What differentiates machine learning is that the associations in question do not need to be specified in advance but can rather be 'learned' from the data itself. This allows machine learning systems to discover associations in data without prior knowledge of the domain in question.

Developing artificial intelligence using machine learning

Machine learning involves an algorithm or process that creates a model to describe associations between elements of data known as features and uses this model to predict future events. An example of an algorithm used for machine learning is the artificial neural network or neural net. Described by McCulloch and Pitts 70 years ago, artificial neural networks represent the processing capabilities of human neurons mathematically (McCulloch and Pitts, 1943). With greater computing power and more data, the tasks performed by artificial neural networks have become increasingly complex, ranging from image recognition to automated driving. Recent advances are attributable to deep neural networks (depth referring to the number of 'neuron' layers) and a technique known as deep learning.

In deep learning, an algorithm is designed to learn associations in data without prior assumptions regarding the distribution of the data. This is achieved by multiple levels or layers of processing with a technique known as backpropagation. This is used to change the representation of data in each layer based on representation in the previous layer by altering the relationship between virtual neurons to optimize an error function (LeCun et al, 2015). This means that deep learning is theoretically more appropriate to complexity of clinical practice than statistical methods that are currently used in research studies. Deep learning requires more data to uncover true (*vs* chance) relationships in data – typically tens of thousands to millions of patients rather than the hundreds or thousands that are typical in biomedical research.

Whether deep learning or not, the most common form of machine learning is supervised learning. Supervision in this instance is a human who labels data items with their category (e.g. radiographic images as fractures or non-fractures). A supervised learning system is then able to modify its internal parameters to define the optimal combination of inputs (e.g. the appearance of a radiograph determined by the individual pixels in an area of interest) to generate the output (fracture diagnosis).

Artificial intelligence and health care: the status quo

There are four areas where artificial intelligence can facilitate patient care:

1. Diagnosis: inference based on data (in the form of symptoms, signs and investigation results)
2. Management: implementing and monitoring a process to achieve a therapeutic endpoint
3. Research: better understanding disease, refining optimal management and developing therapeutics
4. Systems analysis: ensuring that resources are allocated in an efficient manner.

Regarding diagnosis, machine learning systems can now diagnose and identify the vertebral level of compression fractures with a sensitivity of 95.7% compared to a board-certified radiologist with 10 years' experience. Furthermore, grade of height loss and fracture morphology were determined with agreement of 68% and 95%, respectively, compared to radiologist assessment (Burns et al, 2017).

In disease management, machine learning can guide management of patients by providing a patient-specific predicted rate of postoperative complications following lumbar fusion surgery. Kim et al (2018) first trained their artificial neural network model using 70% of a dataset of 22 629 patients, and then assessed their model using

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the remaining 30% of their dataset. They found that neural networks were more successful than a patient's American Society of Anesthesiologists classification at predicting events such as venous thromboembolism and wound complications. As such, it can be implied that a physician, such as a junior radiologist, or an institution, such as a low-volume spinal centre, would benefit from the knowledge transfer facilitated by artificial intelligence solutions. Adopting such diagnostic and management tools has the potential to reduce the variability in practice and outcomes described earlier. Artificial intelligence is also being used in academia to help physicians identify hitherto unknown tumour subtypes (Vural et al, 2016), and is accelerating discovery in drug design (Schneider, 2017), genetics (Libbrecht and Noble, 2015) and immunology (Andreatta et al, 2017).

That said, there has been little progress in the fourth domain: use of artificial intelligence for optimization of a health system. This reflects the novelty of the technology and the lack of availability of requisite data and resources in governments, public health bodies and provider organizations.

However, it is important to appreciate these advances for what they are – examples of learning by brute force in a single domain. While the promise of these new benchmarks in performance is considerable, it is important not to overgeneralize the applicability of advances in constrained environments to the variegate complexity of processes found in a typical health system. This is not to diminish these achievements, but rather to acknowledge that they are instances of a brute force exercise in data analysis that have been successful in finding patterns of predictive value. The development of general artificial intelligence is not an immediate prospect. As such, the idea of artificial intelligence-powered robots replacing clinicians en masse is fanciful. However, the prospect of machine learning enhancing the work of clinicians in defined areas while achieving a more optimal and arguably enjoyable skill mix in the clinical team is tangible, potent and achievable in the near future.

Artificial intelligence across the care continuum: potential applications in orthopaedics

Orthopaedic services are a lattice of clinical processes that together create health outcomes for patient populations. These processes involve significant collaboration with community-based colleagues and actions that the patient conducts herself or himself before presenting to primary or secondary care, as well as after definitive intervention, such as surgery, to enable return to premorbid functioning. Process management as a formal discipline in medicine is relatively new and even though processes have been defined in orthopaedics, it has remained challenging to collect data with minimal latency and in requisite numbers to enable the optimization of processes at scale (Maggard-Gibbons, 2014). With the ubiquity of formal clinical pathways across orthopaedics, proposed data sharing with primary care and digital health tools that include the patient as producer of outcomes data make it possible to address this issue of scale (Flikweert et al, 2014).

Artificial intelligence, then, offers a compelling means of making sense of data from clinical processes to manage and optimize these processes – i.e. a digital closed-loop feedback system to realize the policy aims of high-quality clinical pathways. This approach has the potential for significant gains across the continuum of care from self-management through the perioperative period to long-term follow up. For example, a patient can be diagnosed in primary care through greater availability of imaging and diagnostic support (both enabled by artificial intelligence), then matched to the appropriate surgeon and subsequently prescribed the appropriate surgical intervention and management plan by the surgeon. The appropriate intervention and plan are based on mining the collective experience of previous similar patients and the data from this new index patient, thus also contributing toward improving future algorithmic inferences. *Table 1* gives an example of the spinal pathway in medical care augmented by artificial intelligence, although a similar approach could be applied to every subspecialty within orthopaedic surgery.

Artificial intelligence and health care: the challenges

In the case of diagnostic artificial intelligence, such datasets already exist in the form orthopaedic imaging and histology specimens. However, in the case of management, research and systems analysis there remains a paucity of robust datasets, although this is changing. Take for example national joint registries. In 2010 data from the UK's National Joint Registry revealed a higher rate of revision surgery in patients that had metal-on-metal hip implants. Subsequently, data from these same registries has helped surgeons better understand why metal-on-metal hip implants tend to fail, the potential implications of metal-on-metal hip implants such as their effect on cancer risk and the patients who are most likely to experience implant failure (Smith et al, 2012). It is easy to envisage a situation, in the near future, when artificial intelligence might be used as an aid by the orthopaedic surgeon to help select the correct implant for his or her patient based on demographics such as age and gender. The key to developing datasets that are fit for artificial intelligence is the early engagement of physicians in general and orthopaedic surgeons in particular. This will ensure that datasets reflect the clinical nuances of orthopaedic surgery.

Artificial intelligence health-care solutions rely on enormous datasets derived from all segments of society. As such, society needs to determine who owns these data. New norms may need to be developed whereby health data are viewed as a public good, and that all individuals should be able to draw on the benefits of algorithms derived from their data. However, this will

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Table 1. Artificial intelligence-enabled solutions in a spinal care pathway

Stage	Artificial intelligence-enabled management
Self-management	Artificial intelligence prognosis based on collective experience of previous patients
	Monitoring of self-management with patient-held digital health tools
	Referral into primary care in accordance with agreed national guidelines
	Ability of pathway service managers to predict demand and staff services, based on real-time monitoring of patient demand
Primary care	Patient flagged for assessment because of failure to progress with self-management
	Evidence-based use of non-operative management such as physical therapy and analgesia
	Artificial intelligence monitoring of patient-held digital health tool to monitor treatment response after visit
	Proactive screening for clinical deterioration (such as neurological deterioration) with automated referral to primary care physician for reassessment
	Magnetic resonance imaging ordered in primary care and analysed automatically using artificial intelligence in community
	Based on positive findings, referral for spinal surgery assessment made by primary care physician decision support tool
	Patient referred to surgery based on artificial intelligence decision support tool (reduction in inappropriate referrals)
Specialist care	Referral screened and investigations requested using artificial intelligence diagnostic tool. Salient data also collected at this stage, e.g. comorbidities and current functional status
	Discussion at multidisciplinary team meeting. Optimal procedure and optimal approach determined using artificial intelligence support based on outcomes of previous cases, e.g. standalone decompression *vs* posterior decompression and fusion
	Patient-specific consent prepared with patient-specific complication profile and prognosis
Preoperation	Monitoring of patient progress with preoperative care delivered using patient-held digital health tool
	Dynamic scheduling of preoperative assessments. Operative date based on patient clinical need and surgical team's operative schedule
	Surgical implants automatically requested
Intraoperation	Computer vision to monitor visual field of surgeon for extent of decompression, neuro-monitoring changes or physiological complications. Automated alerting of surgical and anaesthetic team
Postoperation	Artificial intelligence monitoring of patient in postoperative period tailored to patient and intraoperative parameters and calibrated according to patient progress
Outpatient follow up	Patient discharged with digital health follow-up plan
	Artificial intelligence vigilant system to monitor progress of patient with plan
	Automated referral into primary physician-based care or specialist spinal services, on proactive monitoring of pain control, patient-reported outcome measures and screening for complications
Long-term management	Patient-held digital health tool for long-term health promotion to include longer term monitoring of patient-reported outcome measures related to spinal surgery. Data automatically uploaded to national spinal registry
	Artificial intelligence-enabled automated referral into primary care when recurrence or complications detected

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require investment from governments and health-care providers to ensure high-quality data are available to train algorithms. Algorithms are only as good as the data used to train them and thus are at risk of mirroring our own biases. For example, legal algorithms designed to help judges have proved controversial for potential racial bias, as applied in courtrooms, when assessing defendant risk of recidivism (Spielkamp, 2017). We need to ensure that algorithms used in health care are not similarly flawed, reflecting possible implicit biases with regard to race,

KEY POINTS

- Outcomes following orthopaedic spinal surgery vary widely even as pathophysiology and surgical technique have advanced.
- Artificial intelligence currently exists in many health care solutions and can be valuable in orthopaedic surgery.
- Artificial intelligence can be applied mainly in diagnosis support, care management, research and systems analysis to support efficiency and personalized care.
- Despite technological advances, more work must be done to integrate an abundance of data and support complex care processes.
- Ethical and regulatory considerations must be made with regard to algorithm design and access to patient data that may not be defined by current laws.

gender, obesity or other socioeconomic factors (Danks and London, 2017).

Furthermore, research and development investment needed to develop artificial intelligence solutions require technical expertise and digital infrastructure beyond the means of most provider organizations. In a cost-constrained environment with competing operational priorities, it is difficult for an individual organization or collection of organizations to justify the necessary capital outlay and strategic prioritization. This presents an opportunity for other stakeholders to catalyse progress in this enabling technology. Medical device companies, national governments and universities all have significant incentives to promote the use of artificial intelligence at the front lines of orthopaedics. What is missing is the mechanism to do so and the necessary controls to ensure an optimal result.

Early engagement of orthopaedic surgeons is also important to ensure that the introduction of artificial intelligence is properly framed. Artificial intelligence should be regarded as a tool, helping doctors to provide better care for patients in a manner similar to a new orthopaedic implant or imaging modality. As such, the introduction and use of artificial intelligence should have physician oversight. In particular, it is important to ensure that algorithms do not recommend particular referral pathways or implants in order to maximize the profits of their designers or sponsors, and that patient privacy and equity in allocation of health care resources are upheld. With this is mind, it might be necessary to implement management controls, akin to a firewall, to separate the implementation of artificial intelligence from those that derive monetary benefit from its application (such as pharmaceutical companies and device manufacturers).

As the use of artificial intelligence grows, our relationship with artificial intelligence will change. Currently, artificial intelligence is largely experimental; in the near future it will become a support tool for clinicians enabling decision support for surgical and medical diagnosis and the ability to more accurately calibrate a management plan to a patient's likely prognosis and real-world progress by leveraging the collective experience of other patients as captured in datasets interpreted by artificial intelligence algorithms. In order to enable this, physicians will need to work with artificial intelligence engineers to ensure that algorithms uphold the same ethical standards that underpin medicine, such as respect for a patient's wishes and confidentiality (Char et al, 2018). Related to this is the issue of accountability. If an algorithm suggests a diagnosis or treatment plan that is incorrect, who is responsible: the manufacturer of the algorithm, the purchaser or the individual delivering patient care? An ethical and legal framework needs to be developed defining the relationship of the patient, physician, algorithm and health-care provider so that artificial intelligence is able to operate within well-defined parameters.

Conclusions

The adoption of artificial intelligence within health care is imminent. Just as medical robotics has augmented a surgeon's physical ability to perform complex operations, artificial intelligence promises to enhance a physician's clinical decision making and ability to improve health care processes (Cobb et al, 2006). It is important that physicians recognize the potential of this new technology, and its challenges, so that we can ensure that it serves patients well. In part, this can be achieved through policy and process as described. However, important factors that will determine the clinical applicability of artificial intelligence such as the ability to understand an individual patient's context or the pursuit of social justice are difficult to represent mathematically and are therefore difficult to incorporate algorithmically. As such, clinicians will continue to play a vital role in reconciling the possibilities of science with respect for autonomy and welfare of human beings. Artificial intelligence will not make clinical values redundant, it will make them more important. BJHM

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