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Review

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Has artificial intelligence in spine surgery lived up to the hype? A narrative review of recent approaches, current challenges, and the path forward

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Abstract
Healthcare applications of artificial intelligence (AI) and machine learning (ML) are currently in a stage of exponential growth; however, their adoption into clinical practice across clinical specialties remains uneven. In spine surgery, the presence of challenging clinical problems, advanced intraoperative technologies, and large multi-center datasets positions the field well for the integration of these technologies into the clinic and operating room (OR). Here, we review recent advances in AI/ML applications in several key domains of spine surgery, identify methodological challenges shared by many approaches, and suggest solutions that may lead to these approaches becoming validated, commercialized tools that can reach clinical practice. Ultimately, we aim for this narrative review to help catalyze further progress in the development and commercialization of AI/ML to benefit future spine patients.

Keywords: Artificial intelligence, machine learning, spine surgery

INTRODUCTION
The past decades have seen spine surgery at the forefront of healthcare innovation, with countless advancements in surgical techniques, robotics, and medical devices positively impacting patient care[1-3]. In

parallel, recent advances in artificial intelligence (AI) and machine learning (ML) have already touched nearly every facet of modern life, from industry and transportation to the arts and music. AI and ML rely on large datasets to recognize patterns in data and, when properly deployed, can perform specialized tasks more quickly and accurately than humans. Due to these promises, spine surgeons are looking to AI/ML to usher in the next generation of technical advancements for their patients.

We are currently at an inflection point for the impact of AI/ML in spine surgery. The number of studies on healthcare AI applications continues to grow exponentially[4], a trend that is reflected in spine surgery as well[5]. Furthermore, national funding agencies have established priorities in healthcare AI[6], and the Food and Drug Administration has gained experience in regulating these tools[7]. Simultaneously, private venture funding has grown substantially in healthcare AI[8], but rates of progress have not been equal across applications[4]. In particular, AI diagnostic tools in radiology and pathology have grown faster than other areas of medicine[4], such as the surgical specialties. A better understanding of the landscape of AI/ML in spine surgery could help bridge the gap between research and commercialization of such tools.

Currently, disorders of the spine are among the major contributors to both healthcare costs and disability both in the United States and worldwide[9,10]. Spine surgery is a major contributor to healthcare spending[11,12], and while safety has improved significantly year over year[13], when complications do occur, they cause a substantial impact on patient quality of life and healthcare spending[14]. Due to the wide range of variables that influence patient selection, preoperative planning, intraoperative technique and decision making, opportunities for the potential impact of AI and the possible challenges are high. AI-based tools that could reliably make advances in efficiency, technical proficiency, or complication minimization would have immense clinical and economic impact.

This article provides a targeted primer on AI/ML algorithms and critically reviews select applications of AI/ML to spine surgery. We highlight those that aim to assist in pre-surgical planning, intraoperative assistance, and prediction of postoperative course. These tools span a spectrum of development and commercial deployment, employ a variety of data sources, and interface with clinicians and patients in a number of ways. Through this narrative review, we identify a set of shared challenges facing the field, namely the substantial heterogeneity in patients with spinal disorders, the uncertainty and subjectivity in outcome measures, and the quality and quantity of data available for algorithm development. Finally, we propose solutions to these challenges, which we hope can forecast a path toward incorporating robust AI/ML tools in spine clinics and operating rooms (ORs), thereby achieving the best outcomes for future patients.

AN AI/ML PRIMER FOR SPINE SURGEONS

AI is a group of computational approaches that aim to provide human-level expertise and decision making and predominantly rely on ML, a class of powerful statistical models that recapitulate in silico different facets of human sensory processing and cognition, ranging from vision and language to estimation and prediction tasks[15,16]. While the technical aspects of AI and ML are beyond the scope of this review, we discuss several key concepts that all spine surgeons should familiarize themselves with, as these technologies continue to play an increasing role in our field.

Traditional ML algorithms adapt structured formulas to relate input and output variables and generate future predictions. Common types of these algorithms include logistic regression, decision trees and random forest, and support vector machines[15]. They differ based on the types of input and output variables they can handle, as well as their ability to process noisy and non-linear data, which are prevalent in healthcare applications. The other major class of models is known as 'deep learning', which accounts for the many recent groundbreaking applications of AI. These models leverage artificial neural networks, which can learn complex relationships between their complex input data and generate a wide variety of potential outputs, including text, images, and audio[16]. Compared to traditional ML, deep learning is more powerful but requires massively more data and is specialized for data-intensive tasks such as vision and language processing. On the other hand, traditional ML has straightforward ways for users to understand what variables are most important in making predictions, which is particularly true for the more simple methods[15]. Efforts to understand how deep learning makes predictions and how it weighs input data present an evolving challenge[16].

Another key division among AI/ML algorithms is between supervised and unsupervised approaches. Supervised models require training between inputs and desired outputs using labeled data. The process of annotating and curating such datasets can be cumbersome and is particularly challenging in surgical specialties where patient numbers are low and factors such as patient privacy are essential. Unsupervised models such as k-means clustering instead can find patterns inherent in unstructured data; however, they cannot directly make predictions in the same way that supervised algorithms can[15]. While AI algorithms are advancing at a staggering pace, developing a general framework that outlines both the capabilities and limitations of these models will be critical for spine surgeons in the coming decades.

RECENT AI/ML APPLICATIONS IN SPINE SURGERY

Preoperative planning

Spine surgeons face various clinical and radiographic factors in preoperative planning, which they must parse to make often difficult and subjective decisions about patient selection and surgical approach. AI could augment the ability of clinicians to understand patient disease states, weigh factors such as symptoms and disability, and assess anatomic and pathologic parameters from multimodal imaging.

A number of recent studies have used ML to assist in understanding clinical variability and phenotype in patients undergoing spine surgery. Unsupervised clustering of the clinical metadata of patients with degenerative spondylolisthesis revealed distinct phenotypes of disease severity, which had different levels of postoperative improvement, pain, and satisfaction despite sharing the preoperative severity on imaging[17]. Clustering has also been shown to disentangle the interactions between patient characteristics and surgical procedures in adult spinal deformity. By inputting a variety of variables including clinical, disability, and spinopelvic parameters, the initial clustering algorithm grouped patients based on age and prior surgery, followed by a second clustering step based on the type of surgery performed, yielding distinct groups that vary in terms of the risk/benefit of surgery[18]. In spinal deformity, preoperatively oriented algorithms can also forecast fine-grained aspects of postoperative responses to a standardized scoliosis questionnaire[19]. Together, these studies reveal how AI can uncover patterns in clinical data that could guide preoperative patient counseling or patient selection and maximize quality and value.

Patient imaging is central to preoperative planning in spine surgery and its analysis is one of the most promising applications of AI [Figure 1]. Radiographic analysis includes image segmentation, which refers to the accurate identification and delineation of anatomical structures. Previous work has leveraged deep learning to segment spinal cord structures in a fully automated manner[20,21], performing better than previous state-of-the-art techniques that did not leverage ML[22]. Further studies incorporating data from patients with SCI improved on these initial advances. They can capture and identify lesions that correlate with motor scores at admission[23] and predict thoracolumbar injury classification scores from CT alone, which typically require MR imaging to assess ligamentous integrity[24]. Other algorithms can accurately segment other relevant anatomic structures, including vertebral bodies and discs[25,26], as well as paraspinal

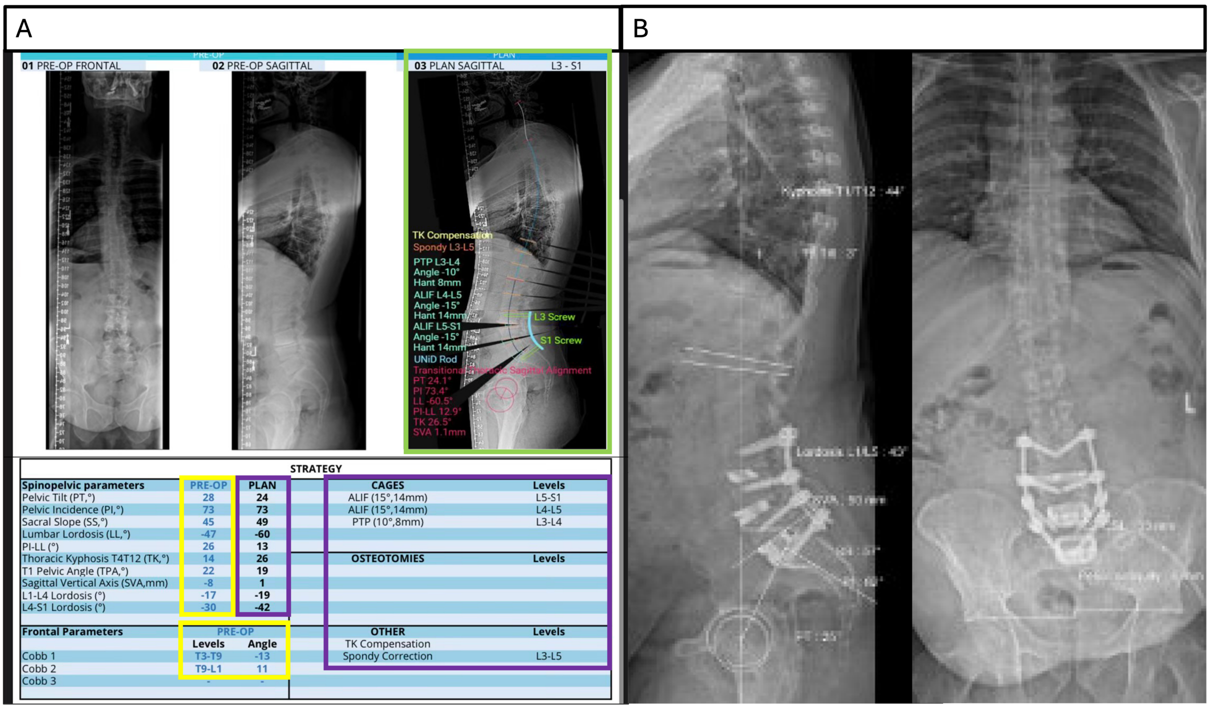

Figure 1. (A) Example of preoperative planning software. Yellow boxes highlight automated spinopelvic parameters and Cobb angle measurements performed by the software. Purple boxes indicate AI-recommended surgical plans and predicted postoperative spinopelvic parameters. The green box demonstrates the predicted postoperative sagittal standing X-ray with the recommended surgical plan; (B) Postoperative standing sagittal and coronal long-cassette radiographs. AI: Artificial intelligence.

musculature[27]. The extent of osteoporosis[28] and associated fractures[29] can also be diagnosed by AI.

Building upon algorithms that segment spinal imaging, others can interpret degrees of neural element compression and estimate parameters of spinal deformity. In particular, these applications are promising as they are tedious, time-consuming, and subject to error and variability when performed by humans. For example, deep learning can estimate the degree of cervical central and foraminal stenosis[30] and can detect lumbar spondylolisthesis[31] and other important aspects of degeneration, such as the degree of disc degeneration and central canal stenosis with high accuracy[32]. For deformity parameter calculation, AI has been applied to calculate coronal[33,34], sagittal[35,36], and combined coronal-sagittal parameters[37]. By incorporating AI into deformity parameter calculation, clinicians can more accurately and efficiently perform both large deformity surgeries and use deformity principles in more limited surgery to ensure patients achieve the best anatomic and physiologic outcomes. These applications represent an ideal area for the strengths of AI to address current challenges in preoperative spine surgical evaluation, and indeed, these technologies have been among the first to reach clinical practice [Table 1].

Intraoperative tools

During surgery, a number of promising AI technologies may help clinicians optimize operative technique and efficiency. Compared to tools designed for pre- or postoperative settings, bringing AI into the OR requires algorithms that can deploy in real time and run on equipment that can interface with the patient, surgeon, and available intraoperative data streams.

Table 1. Summary of studies discussed in the preoperative planning subsection, highlighting key advancements in ML applications for preoperative radiographic and clinical tools

Area of investigation	Selected studies
Utilizing ML clustering methods to identify distinct phenotypes of spinal pathologies, presentation patterns, and radiographic parameters	Chan *et al.*, 2021[17]; Ames *et al.*, 2019[18]
Preoperative counseling based on patient specific factors	Ames et al., 2019[19]
Automated segmentation of anatomical structures from patient radiographs and films	Spinal cord: Gros *et al.*, 2019[20]; Jamaludin *et al.*, 2017[21] Vertebral body and discs: Pang *et al.*, 2022[25]; Pang *et al.*, 2021[26] Paraspinal musculature: Wesselink *et al.*, 2022[27]
Building upon segmentation algorithms to identify clinical correlates (e.g., neurologic exam, osteoporosis, disc degeneration, spinal stenosis)	Neurologic motor scores: McCoy *et al.*, 2019[23] Thoracolumbar injury classification: Doerr *et al.*, 2022[24] Osteoporosis and fractures: Zhang *et al.*, 2020[28]; Yabu *et al.*, 2021[29] Spinal and foraminal stenosis: Jardon *et al.*, 2023[30]; Grob *et al.*, 2020[32] Lumbar spondylolisthesis: Trinh *et al.*, 2022[31]
Automated spinopelvic parameter calculation	Berlin *et al.*, 2023[33]; Wu *et al.*, 2018[34]; Weng *et al.*, 2019[35]; Korez *et al.*, 2020[36]; Galbusera *et al.*, 2019[37]

ML: Machine learning.

Perhaps the main application of AI in the OR is to guide the next generation of surgical navigation, which currently relies on intraoperative radiography and the registration between pre- and intraoperative images. Today's approaches are limited by radiation exposure to the surgical team and patient, delays in operative time caused by acquiring such images, differences in patient anatomy between images acquired in prone and supine positions, and device failure causing navigational inaccuracy.

One promising technology dubbed the Paradigm™ system (Proprio, Seattle, WA) aims to lessen the need for intraoperative CT by using an optical imaging device and computer vision algorithms to align the intraoperative patient with their preoperative imaging, potentially unlocking radiation-free navigation and calculation of spinal anatomic parameters, which could improve safety and speed[38]. Another competing technology, Flash 7D™ (SeaSpine, Carlsbad, CA), also aims to leverage optical imaging-based navigation powered by deep learning and computer vision. These technologies are being applied to instrumentation in lumbar degenerative disease[39], pediatric deformity[40,41], and trauma[42,43], with potential safety benefits and reduced need for fluoroscopy.

Augmented or mixed reality, in which the surgeon wears goggles that permit them to view the operative field with graphic overlays, also leverages devices with the capability of AI-assisted computer vision [Figure 2]. These approaches are under development in spine surgery[44] and also promise to help visualize underlying anatomy[45] to guide pedicle screw placement[46] and to help perform osteotomies. Early research suggests augmented reality (AR)-assisted pedicle screw placement may compare favorably to freehand techniques[47] in spinal deformity cases and is also being studied for screw placement in workhorse approaches such as transforaminal lumbar interbody fusion[48]. Our desire to minimize invasiveness while maximizing visualization of critical structures and accuracy of instrumentation necessitates intraoperative AI to continue making progress [Table 2].

Postoperative prognostication

One of the most common and accessible applications of AI/ML in spine surgery is predicting postoperative outcomes. National datasets from the NIH, American College of Surgeons, and NeuroPoint Alliance, which capture clinical and demographic data, metrics of surgical success, patient-reported outcomes, and complications, can allow clinicians to build models forecasting both perioperative and long-term outcomes

Table 2. Summary of studies discussed in the intraoperative tools subsection

Area of investigation	Selected studies
ML and computer vision tools for optical image-based intraoperative navigation (reduce radiation exposure)	General technique: Berven *et al.*, 2023[38] Lumbar degenerative disease: Abdelrahman *et al.*, 2022[39] Pediatric deformity: Comstock *et al.*, 2023[40]; Lim *et al.*, 2023[41] Trauma: Yeretsian *et al.*, 2022[42]; Malacon *et al.*, 2022[43]
Intraoperative AR, VR, and mixed reality tools	Eliahu *et al.*, 2022[44]; Auloge *et al.*, 2020[45]; Burström *et al.*, 2019[46]; Elmi-Terander *et al.*, 2020[47]; Charles *et al.*, 2021[48]

ML: Machine learning; AR: augmented reality; VR: virtual reality.

Figure 2. Percutaneous lumbar pedicle screw placement assisted by AR headset (yellow arrow). The green box highlights the AR overlay, which displays the screw trajectory, allowing the surgeon to maintain focus on the operative field without needing to look at monitors. AR: Augmented reality.

at the patient level. These methods may help identify risk factors that lead to poor outcomes, allowing surgeons to better select patients and tailor appropriate surgical interventions and postoperative care.

A broad spectrum of ML studies have aimed to predict perioperative patient outcomes and complications and identify variables that most strongly drive these events. ML tends to identify common factors that correlate with perioperative outcome, such as age, functional and nutritional status, BMI, Medicaid status, intraoperative blood loss, smoking, and preoperative medical comorbidities, but the exact predictors vary by study[49-53]. Some models tend to predict relatively common events such as postoperative delirium, hospital readmissions, and length of stay, whereas others aim to predict rarer and potentially more catastrophic events such as vascular injury during anterior lumbar surgery[51]. Across tools that aim to quantify adverse events, the approaches that are trained on large databases, receive external validation and testing, and release their tools as open source or commercialized software are most likely to gain the most traction.

In addition to perioperative complications, ML is also well-suited to predict long-term outcomes. In cervical spondylotic myelopathy, previous studies have accurately predicted outcomes years after surgery from preoperative variables, with simple methods such as logistic regression performing well compared to more advanced methods[54,55]. By examining feature importance methods in ML algorithms, drivers of long-term outcomes can be better understood. For example, in patients who underwent lumbar fusion, higher leg pain and back pain preoperatively were predictive of improvements in leg and back pain, respectively[56]. In a separate study of both cervical and thoracolumbar fusion, preoperative axial pain and peripheral pain, nationality, the number of previous spine surgeries, age, type of intervention, preoperative quality-of-life, BMI, number of affected levels, and comorbidity were major predictors of outcome[57]. Similarly, using preoperative MRIs, one study used neural network-based models to predict postoperative proximal junctional kyphosis (PJK). Analysis of the model found that soft tissue features were the strongest drivers of the accuracy of PJK prediction[58]. A natural question is to ask: "How valuable are these models?" Indeed, they primarily identify obvious risk factors as drivers of short-term complications (age, sex, comorbidities), and those of long-term outcomes (how much patients stand to gain from their preoperative level of disability). We argue that the key to these models is to be able to quote and counsel patients about risks and outcomes in a patient-specific manner to improve informed consent and shared decision making [Table 3].

CHALLENGES AND OPPORTUNITIES

AI and ML tools throughout the spectrum of spine surgical care hold significant promise to improve patient outcomes; however, those at each point of care have sets of unique challenges. AI/ML focusing on preoperative planning may require prospective studies showing that it improves outcomes to gain traction from physicians and reimbursement from insurance companies. Intraoperative tools and robotics require significant hardware investment and may face regulatory challenges to reach clinical integration, and may encounter resistance from surgeons who fear inefficiencies and potential patient harm associated with early adoption of new technologies[59,60]. Models that predict postoperative complications and long-term outcomes face difficulty in standardizing outcome metrics and in generalizing across centers[61. However, common to all AI/ML tools in spine surgery are several critical challenges, which we detail below, along with our proposed solutions.

Challenge 1: patient and surgical heterogeneity

Our varied clinical and research efforts in spine surgery reflect the immense heterogeneity in the patients we treat. Patients may undergo the same operation for a wide variety of indications, at a wide variety of initial states of health, and similarly, outcomes are driven by a wide variety of physiologic and psychosocial factors. In addition, the same patient with the same pathology may be offered differing surgical plans based on their surgeon's training and preference. A central challenge in ML is the tradeoff between variables and observations (i.e., patients)[15]. In spine surgery, where patient variability is high, this limitation means that for models to reach the expert level, they must incorporate both many variables and data from a large number of patients. However, as model complexity increases, the ability to understand such models decreases. To mitigate this tradeoff, it may be most expedient to focus AI development efforts on applications that are specifically tailored to quickly and accurately perform highly specific, otherwise time-

Table 3. Summary of AI/ML studies discussed in the postoperative prognostication subsection

Area of investigation	Selected studies
Perioperative complication prediction and risk stratification	General technique: Berven *et al.*, 2023[38] Lumbar degenerative disease: Abdelrahman *et al.*, 2022[39] Pediatric deformity: Comstock *et al.*, 2023[40]; Lim *et al.*, 2023[41] Trauma: Yeretsian *et al.*, 2022[42]; Malacon *et al.*, 2022[43]
Long-term outcome prognostication	Eliahu *et al.*, 2022[44]; Auloge *et al.*, 2020[45]; Burström *et al.*, 2019[46]; Elmi-Terander *et al.*, 2020[47]; Charles *et al.*, 2021[48]

AI: Artificial intelligence; ML: machine learning.

consuming tasks (i.e., image segmentation of the spine or robotic navigation).

Challenge 2: subjective outcome measures

Despite the aforementioned challenges in developing a broad AI understanding of spine surgery arising from patient heterogeneity, one substantial barrier lies in challenges presented by current outcome measures. Many of the endpoints we follow are subjective or are influenced by a wide variety of factors that AI may not be able to accurately capture in an unbiased manner. For example, endpoints such as pain and functional status may be influenced by psychological factors. Endpoints such as the return to work may be influenced by socioeconomic status. Endpoints such as the need for revision surgery may be influenced by many factors, including preoperative comorbidities and postoperative access to care in addition to the surgery itself. Postoperative pain medication use is influenced by preoperative levels of tolerance and patterns of clinical prescription. It is critical that such models and their predictions do not lead clinicians to select patients or surgical approaches in a way that perpetuates present disparities. Solutions to this problem may be to focus on more immediate rather than long-term measures, on quantitative or radiographic endpoints that can be measured in a validated manner, and potentially to use AI and new technologies to develop novel outcome metrics that better capture the impact of spine surgery on patients' lives.

Challenge 3: tradeoffs in data quality and quantity

One of the central principles of ML is that capabilities and performance increase with ever-larger datasets[15]. In particular, cutting-edge approaches such as deep learning and large language models (the types of models underlying self-driving cars and ChatGPT, respectively) rely on immense amounts of data to tune hundreds of billions of parameters, from which their intelligence emerges[62]. In spine surgery, large registries such as the Quality Outcomes Database (QOD), British Spine Registry, and International Spine Study Group (ISSG) have aggregated patient data across numerous centers, and the largest ML studies may incorporate thousands of patients. However, these numbers are likely sufficient for certain tasks requiring only simple categorical and numerical variables as inputs rather than complex data such as cross-sectional images, text, and video that require immense amounts of data. Still, healthcare databases often encounter quality issues such as missing or incomplete data and variable practices across the sites where the data were collected. Furthermore, as the number of variables per patient in the database increases, the difficulty of expanding the dataset grows, limiting the number of patients incorporated and increasing the administrative burden on centers that participate.

Due to limitations in data quantity, many studies are validated using withheld patients or cross-validation from the same single-center datasets, which may result in model overfitting and limited clinical utility. Validation using independently collected external datasets will allow for improved assessments of model accuracy and generalizability. Even findings from multi-center studies may be affected by this problem, as the datasets are not completely independent of one another. In addition, some studies used large national datasets that may have limited granularity of clinically relevant variables, potentially limiting their models' performances. We propose that the standards for multi-center validation and held-out validation and test sets for quantifying performance - standards commonly applied across AI applications - be rigorously applied in AI tools for spine surgery to ensure that published models have the best chance for successful clinical translation.

Future directions

While challenges remain in further integrating AI and ML technologies into spine surgery practice, these technologies have already made an impact on clinical care, operative planning, and procedures in the OR. For AI technologies to continue to develop, the field of spine surgery must make a concerted effort to collect high-quality data in the form of de-identified or HIPAA-compliant large multi-center databases and registries, as these data can be used to fine-tune existing and develop new AI technologies. Future surgical planning and prognostication models should leverage a wide variety of data sources for model training, ranging from demographic and clinical data to patient radiographs and free text from medical records. In addition, surgeons should work closely with industry and academic partners to create robotic and augmented/mixed reality tools. As with all new technology, these efforts will require careful oversight, fine-tuning, and comparison to existing best practices. Should spine surgery as a field successfully apply AI models and tools, our patients stand to benefit the most through patient-specific, data-driven surgical planning tools, increased surgical efficiency, and more accurate short and long-term prognostication.

CONCLUSION

This narrative review highlights a selection of current developments in AI for spine surgery. Despite the challenges discussed in the previous section, AI is already beginning to change how we practice spine surgery. By understanding the current landscape of AI/ML tools across stages of development and clinical scenarios ranging from pre- to intra- and postoperative contexts, we may target our efforts toward incorporating the methods most pertinent to the challenges in our practice. One can easily imagine a near future where AI assists in planning surgical approaches and counseling patients, integrates into intraoperative imaging and navigation systems to enhance anatomical recognition and guide instrumentation, and helps avoid and manage postoperative complications. By highlighting the path forward, we identify strategies that innovation-minded spine surgeons can adopt to expedite the development and clinical translation of these models for the benefit of our patients.

DECLARATIONS

Authors' contributions

Made substantial contributions to the drafting of the article: Ambati VS, Saggi S, Alan N
Made substantial contributions to background research and review of existing literature: Ambati VS, Saggi S, Dada A
Led the review article (supervising/senior author): Alan N

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Alan N serves as a consultant for Globus, Stryker, and Depuy Synthes. The other authors declared that there are no conflicts of interest.

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