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THE INTEGRATION OF ARTIFICIAL INTELLIGENCE IN SPINAL CARE ASSESSMENT AND SURGERY: A COMPREHENSIVE NARRATIVE REVIEW

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ABSTRACT

Artificial intelligence (AI) and machine learning (ML) are driving a paradigm shift in spine surgery, augmenting surgical decision-making with data-driven insights. This review synthesizes the current landscape of AI applications across the surgical care continuum and evaluates its potential to enhance precision, personalization, and value. A narrative review was conducted through a critical analysis of contemporary literature, including original research, systematic reviews, and editorials from high-impact orthopaedic and spine surgery journals. Key themes were identified and organized to provide a coherent overview of AI's role in preoperative planning, intraoperative execution, and postoperative economics. AI demonstrates significant utility in automating spinal imaging analysis, with convolutional neural networks enabling rapid vertebral segmentation and accurate measurement of alignment parameters. Predictive ML models excel in forecasting individualized patient risks, with specific algorithms outperforming surgeons in predicting complications and long-term outcomes. Intraoperatively, AI-driven navigation and robotic systems achieve a pedicle screw placement accuracy exceeding 94% while reducing radiation exposure. Furthermore, AI applications are emerging in health economics, effectively predicting costs and automating administrative tasks. Despite this, various challenges continue to hinder progress, notably the black-box nature of algorithms, data bias, ethical dilemmas, and barriers to clinical adoption.

The available evidence positions AI not as a proven superior alternative, but as a promising adjunct with proof-of-concept applications across the spine care continuum. AI serves as a powerful adjunctive tool in spine surgery, promising to enhance procedural precision, personalize patient care, and improve economic efficiency. While limitations regarding transparency, data diversity, and ethical frameworks must be addressed, the ongoing development of explainable AI and robust datasets indicates a transformative future for spinal surgical practice. To ensure safe and equitable adoption, the next steps require prospective multicenter validation, active surgeon participation in governance and education, and global collaborations to develop diverse datasets.

Keywords: Artificial intelligence, machine learning, spine surgery, predictive analytics, surgical navigation, value-based care, explainable AI

INTRODUCTION

From its conceptual origins in Alan Turing's theoretical work of the 1950s, artificial intelligence (AI), characterized by its capacity to emulate human intelligent behavior, has matured into a transformative force within modern healthcare. The foundational event was the 1956 Dartmouth College conference, which formally established AI as a field of study. Machine learning (ML), a core element of AI, allows systems to learn from experience and enhance their performance by discerning complex relationships in data, thereby producing inferences and predictions without being explicitly programmed for every individual scenario. The rapid expansion of literature, technology, and clinical use makes understanding AI/ML applications increasingly imperative in spine surgery, where their capacity for sophisticated pattern recognition and prediction is uniquely suited to the field's intricate and multifactorial nature (Figure 1)[1].

The management of complex spinal pathologies, such as adult spinal deformity (ASD), tumors, and infections, demands the synthesis of a vast array of factors, from intricate radiographic parameters and biomechanical considerations to patient-specific comorbidities and goals, making surgical decision-making a highly nuanced process, particularly for conditions like ASD which require a holistic assessment of

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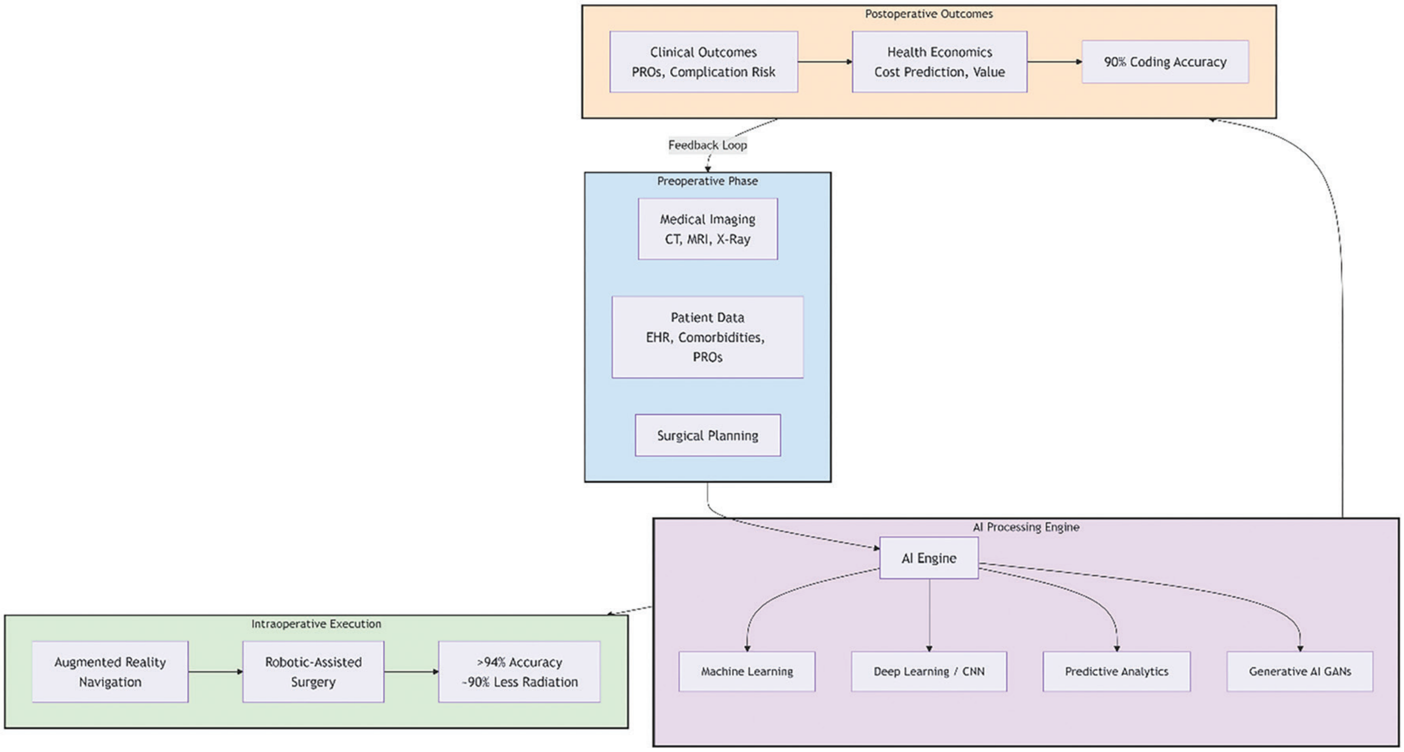

Figure 1. Workflow of AI integration in spine surgery
This schematic illustrates the continuous, cyclical framework of AI integration across the core phases of spine surgical care. The model is built upon a continuous learning feedback loop (grey arrow), where postoperative outcomes are used to refine and improve the AI algorithms, creating a system that evolves with each case. Preoperative phase (blue): the process initiates with the synthesis of multifaceted preoperative data, including medical imaging (X-Ray, CT, MRI, EOS), patient-specific variables from EHRs (comorbidities, demographics), and PROs. This data informs the initial surgical planning. AI processing engine (central purple hub): the raw data is processed by a central AI engine utilizing a suite of ML methodologies. These include supervised learning for predictive analytics, deep learning (e.g., CNNs) for image segmentation and analysis, and generative AI (e.g., GANs) for data augmentation and synthetic image generation. Intraoperative phase (green): the AI-generated surgical plan is executed with enhanced precision in the operating room. AI-driven technologies such as AR navigation systems and robotic-assisted surgery platforms translate the preoperative plan into action, significantly improving the accuracy of instrument placement (e.g., >94% for pedicle screws) and drastically reducing radiation exposure (e.g., by up to 90%) for the patient and surgical team. Postoperative phase (orange): the outcomes of surgery are quantitatively measured, capturing both clinical endpoints (e.g., complication rates, achievement of MCID in PROs) and health economic metrics (e.g., resource utilization, cost prediction, automated medical coding). This data is the crucial output that feeds back into the system. Feedback loop (grey): postoperative outcome data is aggregated and used to retrain the AI models in the central engine. This closed-loop system ensures continuous refinement, validation, and improvement of the predictive algorithms and surgical planning tools, ultimately leading to progressively superior, personalized, and value-based patient care. AI: Artificial intelligence, CT: Computed tomography, MRI: Magnetic resonance imaging, EHRs: Electronic health records, PROs: Patient-reported outcomes, ML: Machine learning, CNNs: Convolutional neural networks, GANs: Generative adversarial networks, AR: Augmented reality, MCID: Minimal clinically important difference,

the entire skeletal structure for comprehensive radiographic evaluation[2]. While traditional statistical methods are powerful for hypothesis testing and establishing associations in well-understood domains with structured datasets, such as public health, ML is better suited for generating individualized predictions from high-dimensional data in innovative fields like omics, radiodiagnostics, and personalized medicine. AI and ML algorithms excel in this predictive capacity, offering the potential to personalize care, enhance surgical precision, improve risk stratification, and optimize resource allocation. As emphasized by Ali et al.[3] technologies are driving significant transformations in spinal surgery. Neural networks enhance the accuracy of preoperative planning, while the use of augmented reality refines intraoperative navigation and reduces radiation exposure. Furthermore, postoperative predictive analytics enable risk stratification, thereby enabling improved precision in surgery, optimization of clinical workflows, and personalization of patient care.

The drive for innovation is further underscored by the alarmingly high complication rates in complex procedures. Effective presurgical planning must address critical patient-specific risk factors, such as age, body mass index (BMI), smoking, and osteoporosis, to mitigate complications, as evidenced by Akıntürk et al.[4] whose analysis of 26,207 patients revealed a

34.5% complication rate predominantly from implant failure (e.g., screw loosening, junctional kyphosis), neurologic deficits (10.8%), infection (3.6%), and cardiopulmonary events (4.8%), all of which adversely impact patient outcomes, length of stay, and readmission rates. This stark reality necessitates moving beyond traditional risk assessment and underscores the critical need for tools that can optimize every phase of care, from patient selection to postoperative management.

The proliferation of large, multi-institutional datasets, enhanced computational resources, and advanced algorithms are accelerating the adoption of AI in spine surgery, where it is enhancing diagnostics, increasing surgical precision, and enabling personalized rehabilitation through early risk assessment and adaptive therapies, despite persistent challenges such as data limitations and ethical considerations[5].

The aim of this review is to synthesize recent literature findings and provide a comprehensive overview of the current state of AI in spinal surgery. It will explore the fundamental types of ML, detail its applications in imaging, surgical planning, outcome prediction, and health economics, and discuss the significant ethical and practical challenges that must be addressed for its successful integration into routine clinical practice.

MATERIALS AND METHODS

This narrative review was conducted through a synthesis of contemporary literature identified from the provided articles, which represent a cross-section of recent editorials, reviews, and original research in high-impact orthopaedic and spine surgery journals. The provided documents were systematically analyzed to extract information on the principles of AI/ML, specific applications in spine surgery (e.g., imaging, prediction models, surgical techniques, health economics), and discussed limitations.

Key themes and sub-themes were identified and organized into logical sections to construct a coherent overview of the field. The focus was placed on applications with direct clinical relevance, including:

a. The use of AI for automated measurement of spinal parameters and image segmentation.

b. The development of predictive models for surgical outcomes, complications, and cost.

c. The integration of AI into surgical navigation, robotics, and augmented reality systems.

d. The role of AI in health economics and value-based care.

e. The ethical and practical challenges facing implementation.

This approach offers a comprehensive, detailed analysis of AI's current role in spinal surgery, incorporating the latest consensus and innovations from recent literature.

RESULTS

Fundamentals of ML in Spine Surgery

ML is broadly categorized into four main paradigms: supervised learning, which uses labeled data to map inputs to outputs for tasks such as classification and regression; unsupervised learning, which identifies hidden patterns and structures in unlabeled data through clustering and dimensionality reduction; semi-supervised learning, which leverages both labeled and unlabeled data to improve prediction accuracy when labeled data is scarce; and reinforcement learning, which enables an agent to learn optimal behaviors through environmental feedback based on rewards and penalties, a method particularly suited for complex domains such as robotics and autonomous systems[6]. Understanding these paradigms is crucial for interpreting the literature. Recent reviews have highlighted an increasing emphasis on transparency and interpretability in clinical settings. In this context, explainable AI (XAI) not only provides the underlying algorithmic prediction but also supplies explanations that offer insights into the prediction's reliability[7]. Furthermore, generative adversarial networks (GANs), which employ two competing AI models (a generator and a discriminator) to produce high-quality synthetic data, are emerging as a powerful tool for medical imaging and data augmentation (Table 1)[8].

Supervised Learning: Algorithms are trained on a labeled dataset in which the target output (e.g., "fracture" or "no fracture") is predefined. The model acquires the ability to map input data to their correct labels and is later evaluated on unlabeled datasets to assess its performance. Common supervised models include:

Decision Trees (DT) and Random Forests (RF): These models use a tree-like structure of decisions (e.g., "Is the posterior ligamentous complex intact?") to reach an outcome (e.g., "stable" or "unstable"). RF is an ensemble learning technique that operates by constructing a multitude of DT. This approach improves overall accuracy and mitigates the danger of overfitting, which is common in single DT. They are highly interpretable and have been used for risk stratification and classification, such as the AOSpine fracture classification, need of blood transfusion, preoperative planning/selection, patient type clustering, adverse events and serious complications[5,9].

Support Vector Machines (SVM): SVMs are a supervised learning model used for classification, regression, and outlier detection. Their mechanism involves finding the mathematically optimal decision boundary (hyperplane) that maximizes the margin between different classes in a high-dimensional feature space. These models demonstrate particular efficacy in image-based diagnostic and prognostic tasks, including the classification of disc degeneration and scoliosis types, the automated detection and localization of lumbar spine and vertebral compression fractures, and the prediction of postoperative outcomes[5,10].

Unsupervised Learning: Algorithms process unlabeled datasets autonomously without human guidance, discovering hidden patterns or intrinsic structures. A common application is clustering patients into novel subgroups based on a combination of clinical and radiographic features, which may predict distinct outcomes or complication profiles[11].

Artificial Neural Networks (ANN) and Deep Learning (DL): ANNs are composed of layered, interconnected nodes

Table 1. ML paradigms and algorithms in spine surgery research

Paradigm/concept	Key idea	Common algorithms	Clinical relevance and examples
Supervised learning	Learns a function that maps inputs to outputs using a labeled dataset for tasks like classification and regression.	DT, RF, SVM, linear/logistic regression, neural networks	Classification and risk stratification: RF/DT for AOSpine fracture classification (stable/unstable), predicting need for blood transfusion, adverse events, and serious complications. SVMs for image-based tasks like classifying disc degeneration, scoliosis types, and detecting lumbar spine or vertebral compression fractures.
Unsupervised learning	Identifies hidden patterns and intrinsic structures within unlabeled data through clustering and dimensionality reduction.	K-means clustering, hierarchical clustering, principal component analysis, autoencoders	Patient phenotyping: clustering patients into novel subgroups based on clinical/radiographic features to predict distinct outcomes or complication profiles.
Semi-supervised learning	Leverages both labeled and unlabeled data to improve predictive accuracy where labeled data is scarce.	Label propagation, self-training, generative models	Data augmentation: overcoming annotation scarcity; e.g., a 2.5D U-Net framework with a cascade design and level set function for precise vertebral segmentation, including fractures.
Reinforcement learning	An agent learns optimal behaviors through environmental feedback based on rewards and penalties, suitable for complex domains.	Q-learning, deep Q-networks, policy gradient methods	Robotic surgery: autonomous surgical planning; e.g., SafeRPlan, a DRL approach for pedicle screw placement that achieves >5% higher safety rates under noise.
Deep learning (specialized architectures)	A subset of ML using multi-layered networks to learn complex, hierarchical data representations, often applied in a supervised manner.	CNN, recurrent neural networks, transformers	Medical image analysis and prognostics: CNNs are used for vertebral segmentation, automated Cobb angle measurement, fracture detection, and prognostic modeling (e.g., forecasting postoperative outcomes, relapse after discectomy, mortality rates, and readmissions/reoperations) to aid preoperative planning.
XAI	A suite of techniques designed to make the predictions of complex "black box" models transparent and interpretable to humans.	SHAP, LIME, attention mechanisms	Clinical adoption: providing surgeons with a rationale for a model's prediction of surgical risk or diagnosis to foster trust and facilitate integration into care.
GANs	A framework using two competing networks (generator and discriminator) to produce high-quality synthetic data instances.	Deep convolutional GANs, StyleGAN, CycleGAN	Addressing data scarcity: generating synthetic medical images (e.g., spine CTs/MRIs) to augment training datasets and protect patient privacy.

This table outlines key ML paradigms and AI concepts in spine surgery research, categorizing them by principle, common algorithms, and clinical applications. It demonstrates how these technologies advance diagnostic precision, data-driven planning, and personalized care. ML: Machine learning, AI: Artificial intelligence, DT: Decision trees, RF: Random forests, SVM: Support vector machines, DRL: Deep reinforcement learning, CNN: Convolutional neural networks, XAI: Explainable artificial intelligence, SHAP: SHapley additive exPlanations, LIME: Local interpretable model-agnostic explanations, GAN: Generative adversarial networks, CT: Computed tomography, MRI: Magnetic resonance imaging

(neurons) designed to process input data, mirroring the structure and function of the human brain. DL refers to ANNs with many hidden layers, capable of learning complex, hierarchical representations of data. A specialized type of ANN, the convolutional neural network (CNN), is particularly powerful for image processing. Inspired by the visual cortex, CNNs are adept at processing pixel data and are the backbone of most modern medical imaging AI applications, from vertebral segmentation to automated Cobb angle measurement[12]. Beyond image analysis, CNNs are increasingly employed for advanced prognostic modeling, demonstrating strong predictive utility in forecasting favorable postoperative outcomes, estimating the risk of relapse following discectomy, the diagnosis of cervical myelopathy, calculating mortality rates after surgery for spinal epidural abscess, and predicting probabilities of readmission or reoperation after posterior lumbar interlaminar fusion, thereby directly informing preoperative planning and surgical candidate selection, particularly in complex cases[6].

Semi-supervised Learning: To overcome the scarcity of annotated fracture data in spinal computed tomography (CT) segmentation, Pan et al.[13] developed a semi-supervised 2.5D U-Net framework that leverages both labeled and unlabeled datasets. Their approach incorporates a cascade design aligned with clinical workflows to enhance segmentation precision across vertebrae. In addressing computational constraints, Huang et al.[14] strategically employed 2D network training supplemented with 2.5D inputs to optimize performance. The model utilizes a dual-branch encoder with multi-scale Swin

Transformer modules for improved feature extraction and introduces a level set function to ensure consistency between pixel classification and geometric regularization. This method demonstrates strong performance across evaluation metrics, highlighting the efficacy of semi-supervised learning and advanced architectural designs in medical image segmentation. In a separate clinical prediction task, Park et al.[15] evaluated several supervised ML algorithms to forecast whether patients with cervical spondylotic myelopathy would achieve a minimum clinically important difference (MCID) in neck pain following surgery. They emphasized that model selection should be guided by dataset characteristics and the specific clinical question. For their balanced dataset, precision was identified as the most relevant metric to optimize the identification of true MCID achievers. Logistic regression achieved the highest precision across both short- and long-term follow-up intervals, demonstrating consistent superiority among the tested models and reaffirming its utility for clinical classification problems.

Reinforcement Learning: In their study, Ao et al.[16] introduce SafeRPlan, a safety-aware deep reinforcement learning approach for autonomous pedicle screw placement in robotic spine surgery. This method incorporates an uncertainty-aware safety filter to ensure safe actions, uses pre-trained neural networks to compensate for incomplete intraoperative anatomical information, and employs domain randomization to improve generalization under noise. Experimental results demonstrated that SafeRPlan achieved over 5% higher safety rates compared to baseline methods, even under realistic surgical conditions.

XAI: As AI models, particularly complex DL systems, become more integral to clinical decision-making, the demand for transparency and interpretability has surged. XAI refers to a suite of techniques designed to make the predictions of these "black box" models understandable to human experts. This is achieved by providing insights into the model's confidence, highlighting the features most influential to a decision (e.g., specific image regions in a CT scan), and generating a rationale for its output. In spine surgery, XAI is critical for fostering clinical trust and facilitating adoption, as it allows surgeons to validate an AI's recommendation for fracture classification, surgical planning, or risk prediction before integrating it into patient care[7].

GANs: GANs represent a category of DL frameworks wherein two neural networks operate in opposition, a generator that produces synthetic data instances, and a discriminator that distinguishes between authentic and generated data. Through this iterative competition, the system progressively improves its ability to generate convincingly realistic synthetic outputs. In medical imaging, GANs address the critical challenge of data scarcity and privacy by creating high-quality synthetic spine CT or magnetic resonance imaging (MRI) images[8]. These generated datasets can be used to augment limited training data, improving model robustness and generalizability, or to create anonymized data for research without compromising patient confidentiality. Applications include data augmentation for segmentation models and simulating anatomical variations for training purposes[17].

Applications in Spinal Imaging and Diagnostics

AI has made significant strides in automating and enhancing the interpretation of spinal images, reducing inter-observer variability and surgeon workload.

Automated Vertebral Segmentation and Identification: CNNs form a fundamental framework for diagnostic and therapeutic planning by allowing highly accurate, automated detection and localization of vertebrae in various imaging modalities such as X-Ray, CT, MRI, and ultrasound. These systems significantly outperform manual methods in consistency and precision, reducing the mean absolute error in Cobb angle measurements to less than 3° compared to manual variability of 2.8°-8°. AI-based approaches also demonstrate robustness in analyzing spinal curvature from suboptimal images, such as off-center, angulated, or smartphone-captured images, and support radiation-free scoliosis screening via ultrasound through automatic extraction of anatomical landmarks for 3D spinal reconstruction. Additional applications include quantitative assessment of thoracolumbar compression fractures to inform clinical management[18]. This is crucial for surgical navigation systems, as it allows for automatic registration of the patient's anatomy to preoperative images, facilitating the planning of pedicle screw trajectories. Burström et al.[19] created an automated spine segmentation algorithm for this purpose, based on 3D reconstructions obtained from cone-beam CT.

Classification of Pathology: ML algorithms excel at classifying spinal pathologies through medical imaging analysis, demonstrating particular strength in automatically grading intervertebral disc degeneration according to standardized systems such as Pfirrmann classification, with CNNs achieving remarkable agreement (up to 95.6%) with expert radiologists[20]. These techniques have been successfully extended to identify various spinal conditions including stenosis, fractures, sacroileitis, and tumors. For neural compression pathologies, AI systems analyze morphological features to diagnose disc herniation and nerve root compression with high accuracy and exceptional reliability[21-23]. Additionally, AI models demonstrate sophisticated diagnostic capabilities in distinguishing benign from malignant vertebral fractures on CT scans, matching or surpassing radiology residents' performance, and in grading metastatic spinal cord compression by precisely delineating margins of involvement[24].

Automated Measurement of Radiographic Parameters: AI enables automated measurement of key spinopelvic parameters, including coronal and sagittal vertical axes, as well as key sagittal alignments such as thoracic kyphosis, lumbar lordosis, and the pelvic parameters of incidence, tilt, and sacral slope, from standing whole-spine radiographs. These AI-derived measurements demonstrate excellent agreement with expert surgical assessments, achieving intraclass correlation coefficients exceeding 0.90 and mean absolute errors below 3° or 3 mm, thereby providing a rapid and reliable alternative to manual methods[25].

Generative AI for Enhanced Imaging: Recent advances have introduced the use of GANs for anatomical image reconstruction. Santilli et. al.[26] developed a publicly available GAN model that generates synthetic STIR sequences of the lumbar spine from standard T1- and T2-weighted MRI scans. Expert radiologists assessed these synthetic datasets and judged them to be of comparable or superior quality in approximately 77% of cases, underscoring their potential to streamline and improve imaging workflows for preoperative evaluation. Importantly, the generated images were shown to be diagnostically equivalent to conventional acquisitions while demonstrating superior overall image quality, supporting their possible integration into routine clinical practice.

Predictive Modeling for Surgical Outcomes and Complications

AI enables personalized risk stratification and outcome prediction in spine surgery, advancing the field toward truly individualized patient care (Table 2)[5].

The potential of AI is not merely theoretical but now demonstrates tangible superiority in specific domains. A compelling example lies in outcome prediction, where an algorithm developed by the International Spine Study Group demonstrated 89% accuracy in forecasting risks. This stands in stark contrast to a study of 39 experienced deformity surgeons, whose predictions for the same set of cases were highly discordant and inconsistent, with estimates for complication rates ranging from 0% to 100%. This highlights the inherent limitations of human cognition when processing multivariate data and the confounding role of emotional bias, where a recent negative outcome can unconsciously skew a surgeon's prediction for a subsequent, similar patient. This concept is further explored by Martin and Bono[27], who note that while traditional regression techniques are well-suited for assessing causation, they are poorly optimized for prediction, a gap that ML specifically aims to fill.

Predicting Complications: ML models have been developed to predict a wide range of complications with high accuracy. These include:

Reoperation and Major Complications: ML algorithms synthesize high-dimensional data from clinical, imaging, and patient sources to produce personalized risk assessments and predictions for surgical results. For instance, Scheer et al.[9] developed a model predicting major complications after ASD surgery with 87.6% accuracy, while Pellisé et al.[28] employed random forest models trained on more than 100 variables to forecast major complications, reoperations, and hospital readmissions, with model performance yielding area under the curve (AUC) scores between 0.67 and 0.92. Building upon this, sophisticated ML techniques, including LightGBM and RF, have been leveraged to generate probabilistic forecasts for ideal surgical outcomes. These are defined as a clinically significant enhancement in quality of life without major complications, achieved by incorporating modifiable risk factors into their analytical architecture.

Proximal Junctional Kyphosis/Failure (PJK/PJF): AI and ML models hold considerable promise for predicting PJK and PJF after ASD surgery, with some studies reporting prediction

Table 2. AI for predictive modeling of surgical outcomes and complications in spine surgery

Prediction category	Specific target	Reported performance/key finding
General complications	Major complications, reoperation, readmission	87.6% accuracy; AUC: 0.67-0.92 for various outcomes; forecasts "ideal outcome" (QoL improvement without complications)
Mechanical complications	PJK/PJF pseudarthrosis	Up to 86% accuracy; AUC: 0.89 91% accuracy; AUC: 0.94; identifies adipose tissue biomarkers
Surgical site infection	Postoperative infection	93% positive predictive value; identifies key predictors (modic changes, glucose, etc.)
Other clinical outcomes	Transfusion, length of stay, opioid use	Predictive capability demonstrated
Patient-reported outcomes	MCID on SRS-22, QALYs	Models probability of achieving MCID; predicts QALYs gained; external validation performed
Risk stratification	Novel ASD classifications	Creates patient clusters with distinct risk/PROMs profiles for better selection and counseling
Surgical planning	Upper instrumented vertebra selection, PJK prevention	87.5% accuracy in UIV selection; optimizes surgical angles
Economic outcomes	Catastrophic costs, financial outliers	Identifies high-cost patients (>$100k); AUC: 0.845-0.883 for cost outliers; $469k saved from scheduling AI

This table demonstrates how AI shifts spine surgery from subjective assessment to quantitative, data-driven prediction, achieving high accuracy in forecasting both clinical outcomes and economic value. These models enhance surgical precision and advance value-based care through personalized risk stratification. AI: Artificial intelligence, AUC: Area under the curve, QoL: Quality-of-life, PJK: Proximal junctional kyphosis, PJF: Proximal junctional failure, MCID: Minimum clinically important difference, SRS-22: Scoliosis research society-22 questionnaire, QALYs: Quality-adjusted life year, ASD: Adult spinal deformity, PROMs: Patient-reported outcomes measures, UIV: Upper instrumented vertebra accuracies as high as 86%[29]. For instance, research by Lee et al.[30] and Ryu et al.[31] has shown that random forest models deliver notably high accuracy and AUC values in forecasting PJK/PJF occurrence and pinpointing major reoperation risk factors. Nevertheless, Tretiakov et al.[32] note a critical limitation: although powerful, RF models may overestimate target outcomes in binary classification tasks due to elevated out-of-bag error, underscoring the importance of transparency and rigorous methodology in predictive modeling.

Pseudarthrosis: Recent advances in ML demonstrate strong predictive capabilities for postoperative complications in spine surgery. Johnson et al.[33] identified adipose tissue features on MRI as potential biomarkers for pseudarthrosis risk, independent of BMI. Further advancing this domain, Scheer et al.[34] devised ensemble decision tree-based models capable of predicting PJK/PJF with 86% accuracy (AUC: 0.89) and pseudarthrosis with 91% accuracy (AUC: 0.94) in a multicenter ASD patient population. Similarly, a separate model for predicting pseudarthrosis at 2-year follow-up after ASD surgery demonstrated 91% accuracy[35]. Complementary to these approaches, Wang et al.[36] developed a nomogram model showing clinical utility for predicting pseudarthrosis probability, highlighting the growing sophistication of AI-driven prognostic tools in spinal surgery outcomes.

Surgical Site Infection (SSI): AI demonstrates promising capabilities in predicting SSI risk following spinal procedures. While a systematic review by Ndjonko et al.[37] noted that AI models show potential for excellent classification accuracy in predicting spinal SSI, the authors caution that most studies remain in early developmental stages, and reported performance metrics should be interpreted with appropriate scrutiny.

Other Outcomes: Models also predict transfusion requirements, length of hospital stay, and prolonged opioid use[5].

Predicting Patient-reported Outcomes Measures (PROMs): AI is increasingly used to predict PROMs following spine surgery, with common targets including the modified Japanese Orthopaedic Association score for cervical, Oswestry disability index for lumbar, and scoliosis research society-22 questionnaire (SRS-22) for deformity pathologies, alongside pain assessments like visual analog scale and numeric rating scale. Predictive models incorporate diverse features ranging from demographics and surgical characteristics to preoperative PROMs, imaging findings, and psychosocial factors. Research by Ames et al.[38] and Oh et al.[39] demonstrates ML's capability to forecast quality-of-life improvements, such as achieving MCID on SRS-22 or predicting quality-adjusted life years (QALYs). A significant challenge remains the lack of PROM standardization, which complicates comparison across studies and limits consensus on optimal implementation.

Risk Stratification and Surgical Planning: AI significantly enhances risk stratification and surgical planning in spine care. Unsupervised learning models analyze hundreds of variables to create novel ASD classification systems, predicting distinct risk profiles and patient-reported outcomes to improve preoperative counseling and patient selection. For surgical planning, algorithms automate critical decisions, such as selecting the upper instrumented vertebra with 87.5% accuracy or optimizing the proximal junctional angle to prevent mechanical complications[40].

AI-enhanced Surgical Techniques: Navigation, Robotics, and Augmented Reality

AI is the engine behind several advanced intraoperative technologies that are increasing surgical precision and safety.

Augmented Reality Surgical Navigation (ARSN): ARSN systems, use CNN-based segmentation of intraoperative 3D cone-beam CT images. The system then projects the preoperatively planned screw trajectories directly onto the patient's anatomy via a headset or display, creating an "X-ray vision" effect. This approach has been demonstrated to increase the accuracy of percutaneous pedicle screw placement to over 94%, while significantly reducing radiation exposure compared to conventional fluoroscopy[41]. Recent innovations include marker-less registration that uses deep neural networks to autonomously identify spinal structures and determine their positional configuration in real-time, yielding a median angulation error of 1.6° with a translational error of 2.3 mm at the screw entry site, all without the time and radiation exposure of traditional methods[42].

Robotics: Robotic-assisted spine surgery systems rely on AI algorithms for planning and executing screw placement. The robotic arm guides the surgeon to the pre-planned trajectory based on intraoperative imaging. Studies report optimal placement rates exceeding 97-98%, comparable to the best results achieved with navigation. The robot adds a layer of precision and eliminates human tremor, standardizing a key step of the procedure. A significant learning curve exists; success rates improve and conversions to manual placement decrease with increased surgeon experience[43].

The integration of AI into preoperative planning is becoming increasingly seamless and accessible. Emerging platforms now allow surgeons to upload radiographic images via mobile applications, where algorithms automatically perform all necessary measurements and synthesize relevant risk variables to generate a patient-specific surgical plan. The efficacy of such tools is significant; they have been shown to reduce the risk of critical complications like implant failure and rod breakage following osteotomy from historical rates of up to 22% down to 4.7%, representing a monumental improvement in procedural safety and reliability[44].

AI in Health Economics and Value-based Care

AI advances value-based spine surgery through three core mechanisms: enhancing patient agency via improved health literacy and remote monitoring, automating administrative and operational tasks to reduce costs, and augmenting clinical decision-making through precise diagnostics, surgical planning, and outcome prediction. Despite its potential, AI implementation faces significant challenges including professional resistance, data quality and privacy concerns, and substantial financial investment in infrastructure[45].

Predicting Cost and Resource Utilization: ML models demonstrate significant capability in predicting financial outcomes in spine surgery. Karnuta et al.[46] implemented a Naïve Bayes algorithm that accurately predicts perioperative outcomes, including hospitalization costs, duration of admission, and discharge destination for patients undergoing lumbar fusion procedures, demonstrating good-to-excellent predictive reliability.

Cost-effectiveness Analysis: AI enables sophisticated cost-effectiveness analysis for spine surgery by integrating predictions of QALYs gained with cost projections, creating a robust framework for evaluating economic value beyond mere procedural expenses. Robotic spine surgery demonstrates cost-effectiveness through reduced revision rates, lower infections, decreased length of stay, and shorter operative times.

Operational Efficiency: AI extends its economic impact beyond the operating room into hospital administration, where algorithms can automatically extract billing codes from operative notes with approximately 90% accuracy, reducing financial losses from human coding errors and streamlining healthcare economic infrastructure. Clinically, AI enhances surgical precision through personalized interventions, particularly in scoliosis treatment where analysis of preoperative imagery helps determine the optimal level of surgical intervention tailored to individual patient needs.

DISCUSSION

The adoption of AI in spinal surgery signifies a fundamental transformation, providing new tools to improve care across all stages, including diagnosis, preoperative planning, intraoperative guidance, postoperative management, and health economic analysis. The evidence presented demonstrates that AI is moving from a research curiosity to a tangible clinical tool with validated applications in imaging, prediction, execution, and health economics.

The ability of ML models to analyze vast, complex datasets allows a more nuanced understanding of diseases like ASD. Traditional classification systems are being supplemented by data-driven clustering models that can identify patient subtypes with unique outcome profiles, enabling more personalized and effective treatment strategies. Predictive models for complications and PROMs empower surgeons to conduct detailed risk-benefit analyses with patients, setting realistic expectations and potentially avoiding high-risk surgeries in those unlikely to benefit[1,3,5,6].

In the operating room, AI-driven navigation and robotics are mitigating human error and elevating the level of precision to new heights. The high accuracy rates of percutaneous screw placement with ARSN and robotics promise to improve patient safety and reduce revision rates[41,43]. Furthermore, the reduction in fluoroscopy time benefits both the patient and the surgical team. Recent advancements, such as marker-less registration and machine-vision systems, are pushing this further, reducing radiation exposure by up to 90% and significantly cutting down procedural time[42].

Perhaps most critically for the future sustainability of spine care, AI provides tools for navigating the shift to value-based care. By predicting both outcomes and costs, AI enables a more sophisticated approach to resource allocation and reimbursement, ensuring that interventions are not only clinically effective but also economically viable[47].

However, the path to widespread adoption is fraught with challenges that the spine community must address conscientiously, many of which are underscored in the latest literature (Table 3)[1,3]:

The "Black Box" Problem and the Need for XAI: The complexity of some DL models can make it difficult to understand how a specific prediction was made, which can erode clinician trust. Efforts to improve model interpretability through XAI are therefore not just a technical necessity but a cornerstone for building trust and facilitating ethical clinical adoption.

Data Bias and Equity: If training data is not representative of the broader population (e.g., lacking diversity in race, ethnicity, or socioeconomic status), algorithms can perpetuate and even amplify existing healthcare disparities. Vigilant curation of diverse datasets is essential. Chen et al.[48] pointed to the challenge of limited dataset diversity, which adversely affects the external validity and generalizability of AI-based systems.

Data Privacy and Security: The implementation of such systems necessitates access to vast quantities of sensitive patient health information. Ensuring stringent cybersecurity protocols and strict compliance with data governance regulations, such as the general data protection regulation and health insurance portability and accountability act, is essential.

Validation and Generalizability: Most models are developed and validated on retrospective data from single or limited institutions. Broader external validation in diverse, real-world settings is essential before they can be relied upon for routine clinical decision-making. Mandate external validation in independent cohorts before clinical implementation. Emerging techniques, such as federated learning frameworks, enable continuous validation and model refinement across institutions while preserving data privacy and addressing the central challenge of data heterogeneity.

Clinical Integration and Workflow: Integrating these tools seamlessly into clinical workflows, perhaps through electronic health records systems (EHR) using standards like substitutable medical applications, reusable technologies on fast healthcare interoperability resources, is another significant hurdle that must be overcome to avoid adding to clinician burden[49]. This is particularly relevant given the spine surgery community's historical reluctance to adopt new technologies that are perceived to disrupt established workflows or offer unclear cost-benefit advantages.

Table 3. Challenges and proposed mitigations for AI in spine surgery

Challenge	Description	Potential mitigation strategies
"Black box" problem	Lack of transparency in how complex models make decisions.	Develop and use interpretable ML models; invest in XAI research.
Data bias and homogeneity	Models trained on non-representative data perpetuate disparities and lack generalizability.	Curate diverse, multi-institutional datasets; implement algorithmic fairness audits.
Privacy and security	Risk of breaching sensitive patient health information.	Implement robust encryption; adhere strictly to data protection regulations (GDPR, HIPAA).
External validation	Models may not perform well outside their original dataset.	Mandate external validation in independent cohorts before clinical implementation. Emerging techniques, such as federated learning frameworks, enable continuous validation across institutions while preserving data privacy.
Clinical integration and adoption	AI tools may disrupt workflows; spine surgeons are historically late adopters.	Co-design tools with surgeons; integrate with EHRs via standards like SMART on FHIR.
Ethical/legal liability	Unclear who is responsible when an AI system errs.	Establish clear guidelines for human oversight and accountability; update regulatory frameworks.
De-skilling	Over-reliance on AI could erode surgical skills.	Frame AI as a decision-support tool; maintain emphasis on core surgical training.
Emotional bias in humans	Human predictions are influenced by recent experiences and emotions.	Utilize AI as an objective, data-driven second opinion to mitigate cognitive bias.

This table outlines key implementation challenges for AI in spine surgery, such as the "black box" problem and data bias, alongside proposed mitigation strategies like explainable AI. It provides a balanced perspective on translating algorithmic potential into safe and equitable clinical practice. AI: Artificial intelligence, ML: Machine learning, XAI: Explainable artificial intelligence, GDPR: General data protection regulation, HIPAA: Health insurance portability and accountability act, EHRs: Electronic health records, SMART: Substitutable medical applications, reusable technologies, FHIR: Fast healthcare interoperability resources

Ethical and Legal Liability: The issue of liability arising from errors produced by AI systems, such as a diagnostic error by a CNN, remains legally and ethically unresolved. A framework for human oversight and liability must be established.

De-skilling: There is a concern that over-reliance on AI could lead to the erosion of fundamental surgical skills and clinical acumen among surgeons[50]. AI must be viewed as an augmentative tool, not a replacement for expertise.

Human Factors and Emotional Bias: Beyond processing power, AI systems offer a unique advantage: freedom from cognitive and emotional bias. AI algorithms, devoid of emotional feedback loops, provide consistent, objective predictions based solely on the empirical data of thousands of historical cases, plotting a patient's risk on a precise curve rather than a wide, subjective range.

Limitations and Challenges

The adoption of AI technologies in spine surgery continues to encounter substantial implementation barriers, including the "black box" nature of complex algorithms, which may undermine clinical trust; limited generalizability due to data bias and homogeneity; unresolved ethical and legal concerns regarding privacy, security, and liability; and practical barriers to workflow integration and potential de-skilling. The historical reluctance of spine surgeons to adopt disruptive technologies further complicates implementation. As a narrative review, this study offers a valuable qualitative synthesis but is inherently susceptible to selection bias. Greater transparency regarding the literature search strategy and inclusion criteria would enhance reproducibility. While the review is well-structured and supported by effective tables and figures, the technical descriptions of ML architectures (e.g., CNNs, GANs) may challenge clinicians without a data science background. Incorporating a glossary or expanded contextual definitions could improve accessibility without compromising technical depth. The review thoroughly identifies adoption barriers but would benefit from discussing actionable solutions. Concrete strategies, such as interoperability standards for EHR integration, structured AI training programs for surgeons, and guidance on regulatory compliance, would provide a more practical roadmap for translating AI technologies into clinical practice.

Future Directions

Looking ahead, the role of AI in spinal procedures will probably see a more advanced and seamless integration throughout the care pathway. Current investigations are increasingly directed toward refining intraoperative techniques through real-time feedback, forecasting the most effective surgical strategies, and suggesting customized implants tailored to individual anatomical requirements. The development and adoption of XAI will be paramount to building trust and understanding model decisions. Furthermore, the use of generative AI, like

GANs, for creating synthetic data to augment limited datasets is a promising frontier to combat data bias. The creation of large, diverse, multi-institutional datasets and open-access web applications that integrate ML predictions directly into the clinical workflow represent the next critical steps toward the equitable and practical point-of-care use of AI. For this future to be realized, the spine surgery community must actively engage in the development, validation, and ethical governance of these powerful tools. The journey has just begun, but the fusion of human expertise and AI marks the dawn of a new, more precise, and value-driven era in spine care.

CONCLUSION

AI is steadily transforming spine surgery, shifting practice from an experience-driven discipline toward one that is increasingly supported by objective, data-based insights. Applications in imaging, risk prediction, navigation, robotics, and economic modeling already illustrate how AI can refine precision, tailor treatment, and streamline workflows. Rather than replacing the surgeon, these tools should be understood as complementary, providing consistency and augmenting clinical judgment. For this transformation to progress responsibly, several priorities must be addressed. First, prospective multicenter trials are needed to validate algorithms in everyday clinical environments and across heterogeneous patient groups. Second, active involvement of spine surgeons in AI development and governance will ensure clinical relevance, accountability, and ethical oversight. Third, international cooperation to establish large, diverse datasets is essential to reduce bias and guarantee that innovations benefit patients globally rather than selectively. By combining rigorous validation with professional leadership and collaborative data sharing, AI can move beyond experimental promise to become a trusted partner in surgical care. This integration offers a pathway toward more precise, equitable, and value-driven spine surgery in the years ahead.

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Footnotes

Authorship Contributions

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