North American Spine Society Journal (NASSJ) 24 (2025) 100787

Contents lists available at ScienceDirect

North American Spine Society Journal (NASSJ)

journal homepage: www.elsevier.com/locate/xnsj

Implementation of artificial intelligence (AI) in ASD treatment[1]

Kyriakos D. Chatzis, BS, Peter Tretiakov, BS, Peter G. Passias, MD*

Division of Spine Surgery, Departments of Neurological and Orthopaedic Surgery, Duke Medical Center, Duke University School of Medicine, 40 Duke Medicine Circle, Durham, NC 27710, United States

CME available for reading paper. See footer for additional information.

ARTICLE INFO

Keywords:
Artificial intelligence
Adult spinal deformity
Machine learning
Surgical planning
Predictive analytics
Computer-assisted surgery
Augmented & virtual reality

ABSTRACT

Background: Adult spinal deformity (ASD) surgery remains one of the most complex and complication-prone areas of spine care, with significant variability in outcomes and high complication rates. Recent advances in artificial intelligence (AI) have shown to be promising tools to address these challenges by improving planning, prediction, and personalization. This narrative review explores the role of AI across the surgical workflow for ASD, from preoperative decision-making to intraoperative execution and postoperative care.

Methods: We conducted a comprehensive narrative review of current literature and technologies related to AI in ASD surgery. Focus areas included evidence synthesis, predictive analytics, automated radiographic assessment, intraoperative navigation, patient-specific implants, and digital patient engagement. We also present a representative case example of AI-assisted deformity correction to illustrate practical clinical application.

Results: AI tools have demonstrated strong potential in improving accuracy and efficiency across various domains. Machine learning algorithms outperform traditional statistical models in predicting complications, length of stay, and functional outcomes. Automated radiographic platforms reliably reproduce spinal alignment measurements and support surgical planning. Personalized instrumentation has been associated with improved alignment fidelity. Lastly, Intraoperative AR/VR platforms and AI-enhanced robotics are helping to standardize execution and reduce variability.

Conclusions: AI is redefining the landscape of ASD surgery through its ability to enhance decision-making, reduce variability, and enable personalized, data-driven care. While widespread adoption requires ongoing validation and integration, current evidence supports the clinical utility of AI-assisted strategies in improving alignment outcomes and surgical safety. This review highlights the growing potential of AI to serve as a cornerstone of precision spine surgery.

Introduction

The management of adult spinal deformity (ASD) presents persistent challenges due to its clinical heterogeneity, high complication rates, and significant economic burden. While surgical correction can provide meaningful improvement in health-related quality of life (HRQoL), it is associated with elevated risks of mechanical failure, prolonged recovery, and variability in outcomes [1–3]. Against this backdrop, artificial intelligence (AI) has emerged as a transformative force in modern spine surgery, enabling data-driven, individualized care pathways that enhance virtually all facets of ASD care [3–5].

This chapter reviews the current and emerging applications of AI across the ASD surgical workflow. Through synthesis of recent literature and illustrative case examples, we aim to contextualize the evolving role of AI in promoting more efficient, personalized, and value-based spine care.

Literature evaluation

The exponential growth of scientific literature over recent decades has fundamentally transformed the landscape of evidence-based medicine. The volume of publications continues to rise at an unprece-

---

FDA device/drug status: Not applicable.

Author disclosures: ***KDC:*** Nothing to disclose. ***PT:*** Nothing to disclose. ***PGP:*** Spine: Editorial/governing board (B); JNS Spine: Senior Chair Editorial board (B); JCM: Editorial Board (B).

* Corresponding author. Peter G. Passias, MD, Division of Spine Surgery, Departments of Neurological and Orthopaedic Surgery, Duke Medical Center, Duke University School of Medicine, 40 Duke Medicine Circle, Durham, NC 27710 USA.

E-mail address: pgpassias@yahoo.com (P.G. Passias).

[1] This article is available at: https://www.spine.org/Education/Continuing-Education/Event-Details?MeetingId=%7BF2ADDF82-CFA2-F011-BBD3-6045BDA8E3CB%7D.

https://doi.org/10.1016/j.xnsj.2025.100787
Received 3 July 2025; Received in revised form 24 August 2025; Accepted 25 August 2025
Available online 27 August 2025

dented rate, with systematic reviews, meta-analyses, and randomized controlled trials showing particularly rapid increases in publication frequency [6,7]. The sheer scale of available data presents significant challenges for timely and comprehensive evidence synthesis, often resulting in evidence syntheses that are outdated by the time of publication [8,9]. These challenges have prompted calls for a fundamental rethinking of the evidence synthesis ecosystem with the need for more efficient approaches to knowledge integration. Automation technologies, including large language models (LLMs) and natural language processing (NLP) tools, have emerged as promising solutions to accelerate literature screening and data extraction/synthesis, thereby supporting the development of "living" evidence that can be updated in real time as new data becomes available.

Several emerging AI systems such as PaperQA, Elicit, Consensus, and Undermind leverage advanced algorithms and large language models to extract key insights from full-text scientific literature. These tools offer rapid summarization capabilities by automating labor-intensive tasks such as screening, citation management and data extraction, enabling the generation of concise and structured outputs within minutes. Quantitative analyses demonstrates that these AI tools can reduce abstract screening workload by 55%–64% and achieve 5-6-fold decreases in review time. Additionally, similar studies report over 75% reduction in labor during dual-screen reviews compared to manual methods [10–12].

In parallel, a range of more structured, purpose-built platforms have been developed to support formal systematic reviews. Tools such as Rayyan, Abstrackr, DistillerSR, ExaCT, and RobotReviewer focus on automating discrete review stages including study selection, information extraction and bias detection. These platforms have demonstrated the ability to eliminate 20%–88% of titles and abstracts from human review without missing final included citations, although performance varies depending on tool design and context given [13]. Real-world applications of these systems further validate the promise of AI in evidence synthesis. For example, Michelson et al. demonstrated that a rapid meta-analysis (RMA) incorporating AI could generate clinically relevant outputs in under 30 minutes, with estimated incidence rates comparable to traditional methods [14]. Interestingly, during the COVID-19 pandemic, it was found that the underutilization of AI in systematic reviews was linked to slower processing and reduced publication impact, highlighting the potential aid that these AI models can have when properly integrated [15].

Although LLMs have shown promise, the use of LLMs in current evidence synthesis is not without limitations. Recent scoping reviews highlight that while LLMs can support up to 10 of 13 systematic review steps, fully validated and established applications that match the gold-standard human-led reviews do not yet exist [16–18]. This could be because LLMs are prone to generating hallucinations, lack transparency due to proprietary training data, and do underperform in more complex appraisal tasks when compared to human raters. For these reasons, overreliance on AI may lead to superficial or misleading reviews, particularly when tools are used without sufficient human oversight. The current best option is a human-AI collaboration, rather than full automation, as it yields the highest accuracy and reliability [19].

Ongoing investments in the evidence synthesis ecosystem are increasingly focused on fostering collaboration between artificial intelligence (AI) developers, domain experts, and policymakers. A prominent example is the United Kingdom's recent $70 million initiative to establish "evidence banks," which aims to create robust, continuously updated repositories of high-quality evidence to support clinical and policy decision-making. Such investments reflect a growing consensus that AI should be positioned as an assistive technology, augmenting rather than replacing human expertise in systematic reviews and meta-analyses.

Predicitve analytics and risk stratification

AI and ML have transformed patient selection and surgical planning in adult spinal deformity by enabling individualized, data-driven decision-making. Traditional regression-based models are limited by their reliance on linear associations and population-level generalizations, often failing to capture the complexity and heterogeneity of ASD patients. In contrast, ML algorithms can process high-dimensional clinical, radiographic, and patient-reported data to generate patient-specific risk profiles and outcome predictions [1,20,21].

Recent studies demonstrate that ML-based predictive models, such as LightGBM and random forest, can accurately forecast the likelihood of achieving ideal surgical outcomes, defined as clinically meaningful improvement in quality of life without major complications, by integrating modifiable risk factors [3]. These models have achieved high discrimination and are now being incorporated into web-based clinical tools, allowing for real-time, individualized risk assessment [3,21,22]. For example, Scheer et al. developed a preoperative predictive model using 20 preoperative variables, including age, leg pain, and Oswestry Disability Index (ODI), achieving an accuracy of 87.6% and an AUC of 0.89 [23]. Similarly, Pellisé et al. used random forest models incorporating over 100 features to predict major complications, reoperation, and hospital readmission, with reported AUCs ranging from 0.67 to 0.92 [24]. Lastly, Safaee et al. focused on predicting hospital length of stay (LOS) and achieved 75.4% accuracy using variables such as C7 sagittal vertical axis and number of levels fused [25].

In addition to being able to predict medical complications, predicting mechanical complications such as, proximal junctional kyphosis (PJK), proximal junctional failure (PJF), and pseudarthrosis would be extremely beneficial to clinicians when assessing patients prior to ASD surgery. The Scheer et al. model also developed validated ML models for both PJK/PJF and pseudarthrosis using ensemble decision trees trained on multicenter ASD cohorts. These models achieved high predictive performance with an 86% accuracy (AUC 0.89) for PJK/PJF and 91% accuracy (AUC 0.94) for pseudarthrosis [23].

Risk calculators with over 100 patient-specific inputs are now available on interactive online platforms such as the dual-model approach (preoperative vs. perioperative) described by Pellisé et al. [24] earlier. This model allows clinicians to assess both static and dynamic risk trajectories, with predictive variables including pelvic tilt, walking ability, and lower instrumented vertebrae (LIV). Kaplan-Meier survival curves and AUC metrics further validate these models' robustness.

As shown, the integration of these AI-driven predictive models into clinical practice has already demonstrated improved accuracy in forecasting surgical outcomes and complications. As newer models integrate advanced imaging and soft tissue metrics, physicians will be able to select the optimal surgical candidates, tailoring interventions to maximize benefit and minimize harm [3,26].

Data-driven classification systems

AI-driven unsupervised learning, particularly hierarchical and k-means clustering, has enabled the development of novel ASD classification systems that move beyond traditional radiographic criteria. These approaches can identify distinct patient phenotypes based on multi-dimensional data, including age, prior surgical history, comorbidities, functional status, and even surgical variables. For example, hierarchical clustering has delineated subgroups with unique risk-benefit profiles, facilitating the construction of risk-benefit grids that inform both patient counseling and surgical planning [27].

Recent multicenter analyses have shown that patients whose management aligns with AI-predicted surgical indication are significantly more likely to achieve minimal clinically important difference (MCID) in functional outcomes, underscoring the clinical validity of these classification systems [28]. Furthermore, these data-driven phenotypes have been externally validated and shown to correlate with differential complication rates and quality-of-life improvements, supporting their integration into routine practice [21,27–29].

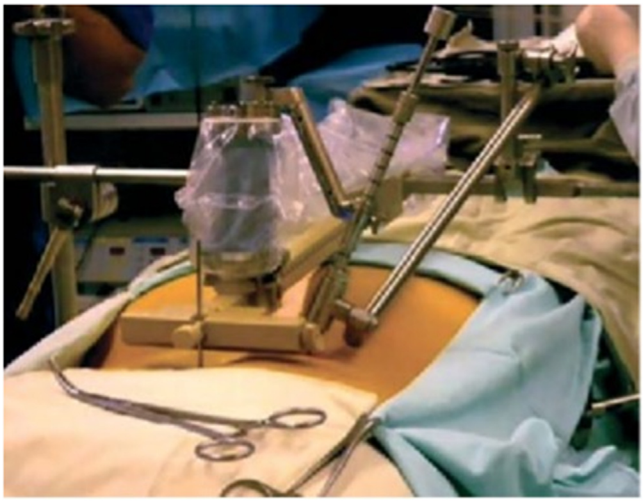


Fig. 1. Mazor Instrumentation during robotic assisted surgery.

Forecasting economic and functional outcomes

In the context of bundled care, precise financial risk prediction is fundamental for sustainable ASD management. Ames et al. demonstrated that regression tree and random forest models can accurately estimate the risk of catastrophic costs (>$100,000) at both 90 days and 2 years postoperatively, with key predictors including surgical approach, number of levels fused, length of stay, and surgeon identity [30]. These models explained a substantial proportion of cost variance and enable actionable risk stratification, supporting the design of risk-adjusted payment models and targeted cost-containment strategies in ASD care.

Integrating these financial risk prediction models with patient-reported outcome (PRO) predictive analytics creates a unified framework for value-based care in ASD surgery. Artificial intelligence-based algorithms, such as those developed by Oh et al. [32], have achieved high accuracy (85.5%) in predicting 2-year minimal clinically important difference (MCID) in Oswestry Disability Index (ODI) scores, while Ames et al. expanded predictive modeling to over 75 variables and multiple algorithms, facilitating nuanced adjustment for provider and technology effects [31,32]. By linking cost predictors (eg, surgical approach, number of levels fused, length of stay, attending surgeon) with models that forecast the probability of achieving MCIDs in outcomes like the ODI, providers and payers can simultaneously assess both the economic and clinical value of surgical interventions [30–32]. For example, patients predicted to incur high costs but with low probability of achieving MCID may be better managed with alternative therapies, while those with high expected benefit and manageable risk can be prioritized for surgery.

Surgical planning

Automated radiographic measurement has emerged as a foundational and impactful application of AI in spine surgery. Early validation studies, such as those by Sardjono et al. [33], established the feasibility of AI systems for automated Cobb angle determination, demonstrating accuracy comparable to manual measurement and setting the stage for further development of automated spinal assessment tools.

Subsequent advances have expanded the scope and clinical utility of these algorithms. For example, Schwartz et al. [34] developed AI-driven pipelines capable of measuring spinopelvic parameters—including lumbar lordosis, pelvic incidence, pelvic tilt, and sacral slope—on lateral lumbar radiographs without requiring manual input, with no statistically significant differences compared to expert-derived measurements, supporting the reliability of these automated methods. More recent models, such as SpinePose, have demonstrated high accuracy and excellent reliability (intraclass correlation coefficients [ICC] 0.91–1.0) across a range of parameters, including sagittal vertical axis, pelvic tilt, pelvic incidence, sacral slope, lumbar lordosis, and T1 pelvic angle, in both internal and external validation cohorts [35,36]. These tools have proven robust even in complex cases, such as severe coronal deformities and

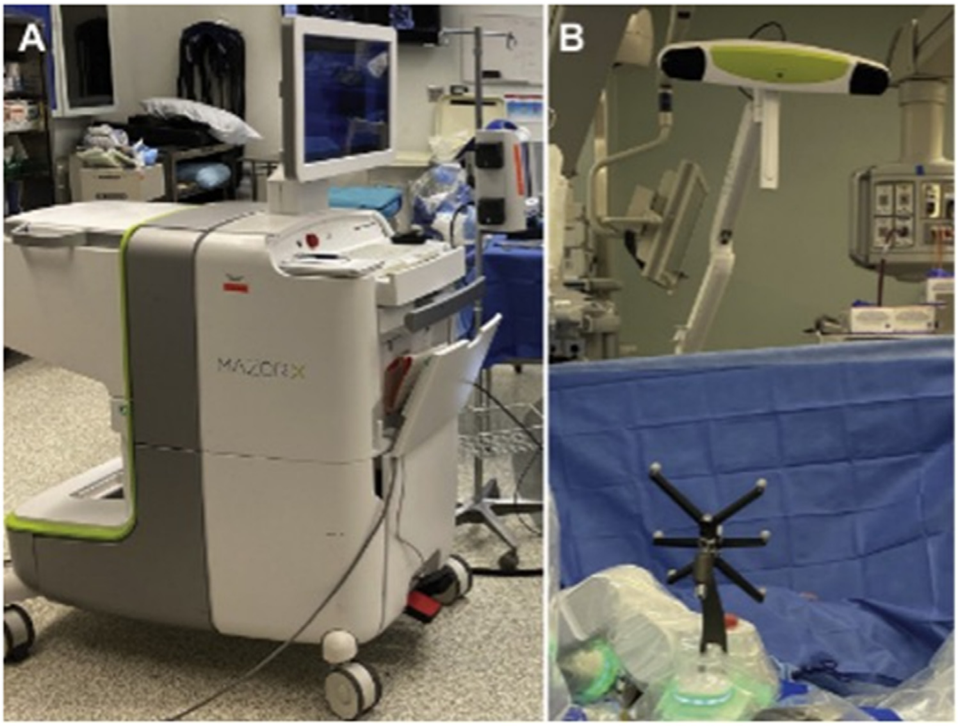


Fig. 2. Mazor X Surgical System Stealth Edition. (A) Mazor X robotic workstation. (B) Stealth camera and reference frame attached to the surgical arm. (Mazor Robotics acquired by Medtronic).

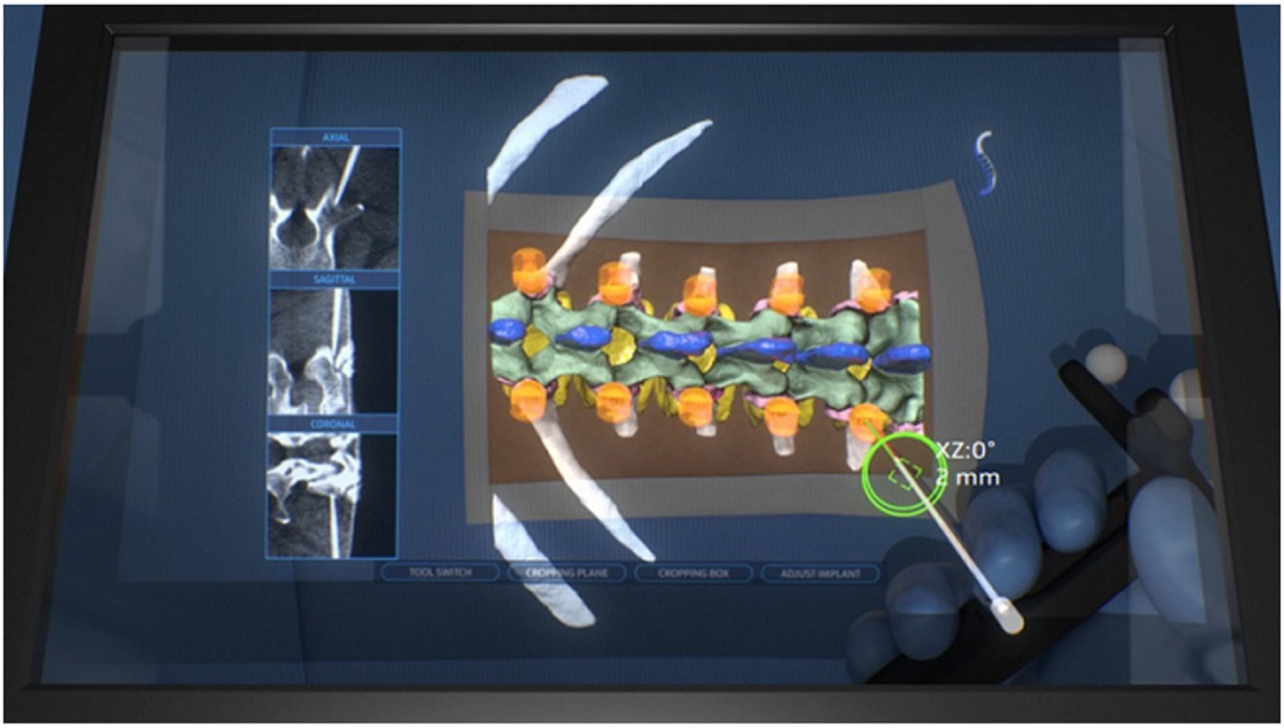


Fig. 3. HOLO Portal intraoperative display showing AI-generated 3D spinal segmentation and planned pedicle screw trajectories, overlaid in real time to guide surgical navigation.

postoperative states, with performance that matches or exceeds experienced orthopedic surgeons [37,38]. The clinical relevance of these findings is substantial. Manual measurement of spinal alignment is time-consuming and subject to inter- and intra-observer variability, which can impact surgical planning and postoperative assessment. AI-based systems enable rapid, reproducible, and objective measurement of key parameters, reducing the burden on clinicians and improving workflow efficiency [35,38–40]. These tools also facilitate large-scale studies and standardization of care and are particularly valuable in settings with limited access to specialized radiologists or high imaging volumes. Importantly, automated measurement systems have demonstrated generalizability across diverse patient populations and imaging protocols, supporting their integration into routine clinical practice [36,38–40].

Beyond measurement, AI and ML have shown promise in also guiding surgical construct selection, an area that traditionally depends on surgeon experience and generalized criteria. In 2021, Lafage et al. [41] developed a machine learning model to predict the optimal upper instrumented vertebra (UIV) in ASD surgery. Their algorithm, which trained on preoperative radiographic data and desired alignment targets, was able to correctly identify the actual UIV selected by expert surgeons in 87.5% of cases. Similarly, Peng et al. [42] focused on predicting the optimal proximal junction angle (PJA) to prevent PJK. They used loading force calculations on cephalad intervertebral discs to derive vertebral stress and then trained a model to predict the optimal construct using these biomechanical data. These studies suggest that AI can standardize complex surgical decisions and potentially reduce inter-surgeon variability, which is a significant step toward evidence-based construct selection and improved reproducibility across institutions [26,29,43]. However, the literature also underscores the need for rigorous external validation and attention to algorithmic bias to ensure equitable and effective integration of AI into surgical practice [44–46].

Historical data-driven approaches have also contributed to this field. Koller et al. [47] analyzed data from 273 patients who underwent anterior spinal fusion (ASF) for selective thoracic scoliosis. They found that preoperative lumbar curve flexibility and 2-year postoperative thoracic curve correction were significant predictors of spontaneous lumbar curve correction (SLCC), which is critical in determining the need for lumbar fusion. These predictors provide actionable metrics that can be integrated into ML models for fusion level selection. These data-driven approaches are shown in work completed by Phan et al. who introduced self-organizing maps (SOM) to classify adolescent idiopathic scoliosis (AIS) cases and guide fusion level selection. Unlike traditional Lenke classification systems, SOM classification does not rely on rigid thresholds such as Cobb angles but instead uses pattern recognition across a large dataset [48]. Their work demonstrated that ML-derived classifications could yield more personalized surgical recommendations with high reliability, as verified by agreement with surgeon-selected constructs. Although these studies were conducted in the setting of AIS populations, the underlying methodologies demonstrate the broader potential of ML in deformity care. Future efforts may adapt these techniques to ASD populations for more personalized fusion level selection.

Collectively, these studies demonstrate that AI-based tools are capable of supporting, and in many cases enhancing, preoperative planning by offering precise measurements, individualized alignment strategies, and optimized construct selection. Importantly, these tools improve reproducibility and reduce subjectivity, particularly in complex cases where minor variations in planning can significantly impact outcomes. As AI continues to evolve, its integration into surgical workflows promises to not only augment surgeon expertise but also promote safer, more effective, and personalized care pathways for patients undergoing spinal deformity correction.

Intraoperative applications

The incorporation of AI into robotic systems has ushered in a new era of precision and personalization in spine surgery. These innovations have enhanced traditional robotic platforms by embedding data-driven decision-making, intraoperative adaptability, and real-time anatomic navigation. The foundational step in this evolution began with the FDA approval of the SpineAssist^{TM} system by Mazor Robotics (Medtronic) in

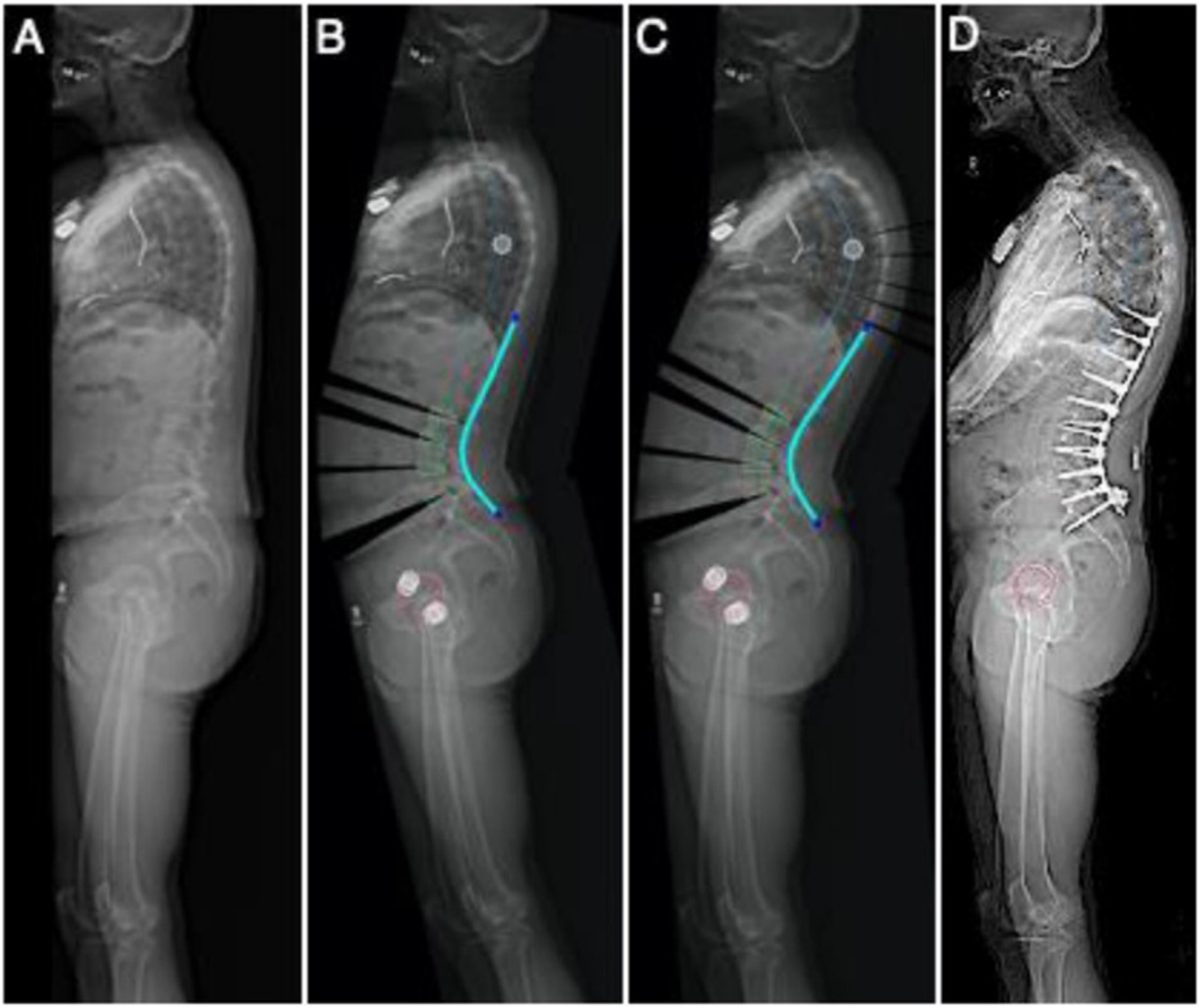


Fig. 4. Pre- and postoperative radiographs showing sagittal correction with patient-specific UNiD^{TM} rods in adult spinal deformity surgery. (A) preoperative, (B–C) AI-generated planning stages, and (D) postoperative outcome.

2004, marking the first AI-guided robotic system designed specifically for spinal procedures. This milestone not only demonstrated the feasibility of robotic-assisted instrumentation in spine surgery but also laid the groundwork for more advanced systems integrating AI and real-time image guidance [49,50] (Fig. 1).

The development of the Mazor X^{TM} system in 2016 significantly advanced intraoperative planning by leveraging preoperative and intraoperative CT imaging for surgical guidance. This system was the first of its kind to offer an independent platform for planning and executing screw trajectories with submillimeter precision [51–53]. In 2018, the integration of Stealth navigation into the Mazor X^{TM} platform allowed for real-time anatomic referencing via a rigid arc fixed to the posterior iliac spine, enabling continuous updates of the surgical plan based on dynamic patient positioning. This fusion of AI with 3D imaging enhanced procedural accuracy while reducing reliance on fluoroscopy, potentially lowering radiation exposure and improving safety [52,54] (Fig. 2). There are now comparable platforms such as ExcelsiusGPS^{TM}, ROSA®, and Cirq® which aim to enhance surgical precision by supporting the registration of surgical tools, mapping surgical corridors, and enabling the dynamic avoidance of surrounding anatomical structures. Recent work by Khan et al. demonstrated that the use of intraoperative 3D imaging significantly improved the accuracy of posterior pedicle screw insertion when compared to traditional fluoroscopic methods [55]. These systems also support broader customization through AI-driven software, which can adapt to a wide range of anatomical variations and operative conditions, thus enhancing surgical flexibility and consistency.

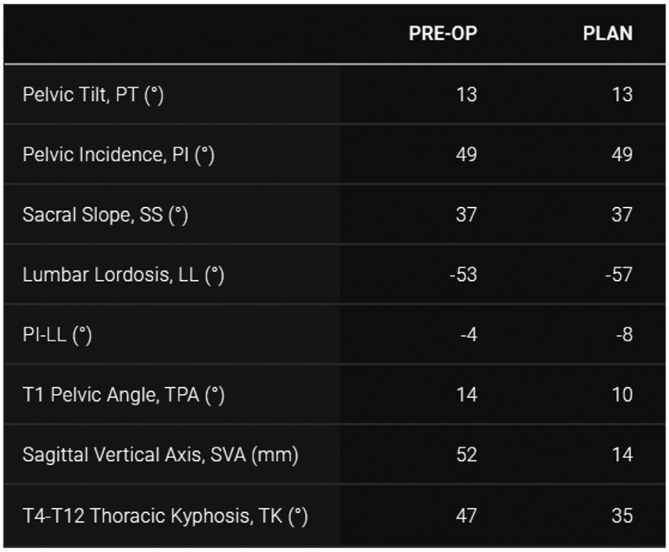
Despite these advancements, the full potential of Computer Assisted Surgery (CAS) systems has been hindered by persistent technical barriers. One major bottleneck lies in the registration process—specifically, the alignment of preoperative imaging data with intraoperative anatomy to generate accurate digital twins. This process is often manual, labor-intensive, and error prone [56–58]. Jecklin et al. [59] proposed a DL solution to address this challenge by estimating 3D vertebral shape from sparse multiview intraoperative X-rays. Their model enabled real-time navigation without the need for extensive manual registration, representing a transformative leap in the efficiency and scalability of CAS platforms.

Beyond navigation, AI modeling has enabled the integration of real-time force feedback, kinematics tracking, and surgical video data into intraoperative systems. ExcelsiusGPS (Globus), for example, utilizes AI to enhance tactile awareness through metrics such as force deflection sensing. This feature aids in the detection of positive surgical margins and potentially preventing intraoperative complications [60–62]. Furthermore, AI-powered analysis of instrument motion and video feeds allows for automated skill assessment and performance feedback. On top of this

Fig. 5. Preoperative standing anteroposterior and lateral radiographs showing thoracolumbar scoliosis, lumbar hypolordosis, and right total hip arthroplasty in a 75-year-old female with progressive sagittal imbalance.

advancement, the rise of AI-augmented reality (AR) systems, such as the HOLO Portal, push the boundaries of visual guidance even more. These systems autonomously segments and labels intraoperative anatomy, allowing the surgeon to visualize planned screw trajectories overlaid onto the patient's actual anatomy in real time. By fusing AI-driven segmentation with AR overlays, these systems offer a 3D holographic representation that enhances depth perception and spatial awareness. This technology allows for intuitive decision-making and efficient execution, particularly in anatomically complex or minimally invasive procedures [4,63,64] (Fig. 3).

Complementing these technologies, virtual reality (VR) has gained recognition as a highly effective educational and preop/intraoperative planning tool. In a randomized controlled study by Shi et al. [65], residents and fellows who trained using VR simulation showed significantly higher accuracy in pedicle screw placement compared to peers trained with traditional methods. Similarly, Gottschalk et al. further validated VR's efficacy by demonstrating improved lateral mass screw insertion among residents in a blinded trial [66]. These results underscore VR's ability to improve spatial awareness and procedural confidence particularly among early trainees or those with limited access to high-volume surgical exposure [67–69]. Experienced surgeons are also turning to VR for complex case rehearsal, particularly in anatomically challenging or revision cases. Custom VR modules, which can be generated from patient-specific imaging data, allow for preoperative walkthroughs of the intended procedure with stepwise visualization of key landmarks, potential hazards, and planned implant trajectories. This form of "digital rehearsal" supports more deliberate intraoperative execution and may reduce operative times, complication risk, and cognitive load [70,71].



	PRE-OP	PLAN
Pelvic Tilt, PT (°)	13	13
Pelvic Incidence, PI (°)	49	49
Sacral Slope, SS (°)	37	37
Lumbar Lordosis, LL (°)	-53	-57
PI-LL (°)	-4	-8
T1 Pelvic Angle, TPA (°)	14	10
Sagittal Vertical Axis, SVA (mm)	52	14
T4-T12 Thoracic Kyphosis, TK (°)	47	35

Fig. 6. AI-assisted (UNiD^{TM} Adaptive Spine Intelligence platform) preoperative planning table showing target alignment corrections.

Together, these technologies reflect a shift from static preoperative plans to dynamic, data-informed, and adaptive surgical environments. The integration of AI with robotic systems, intraoperative navigation, 3D imaging, AR, and VR has created a comprehensive ecosystem that enhances precision and supports both novice and expert surgeons. As these platforms continue to evolve, they are expected to play an increasingly central role in delivering safer, more efficient, and personalized spine surgery.

Patient-specific instrumentation and surgical personalization

Recent advancements in AI-enhanced robotic systems emphasize their potential to refine surgical planning by avoiding overcorrection and reducing the likelihood of adverse postoperative outcomes. These systems analyze large databases of radiographs and postoperative alignment metrics to detect compensatory patterns in the spine and predict patient-specific biomechanical behaviors. One application of this is the generation of AI-designed custom rods. By utilizing radiographs to anticipate thoracic compensation and junctional failure, these rods are tailored to individual anatomical and biomechanical profiles, offering a level of personalization that exceeds conventional instrumentation (Fig. 4).

The limitations of traditional rod bending techniques are well documented, with manually contoured rods often failing to precisely match patient-specific curvature. This can introduce variability in alignment outcomes and increase the risk for rod breakage or construct

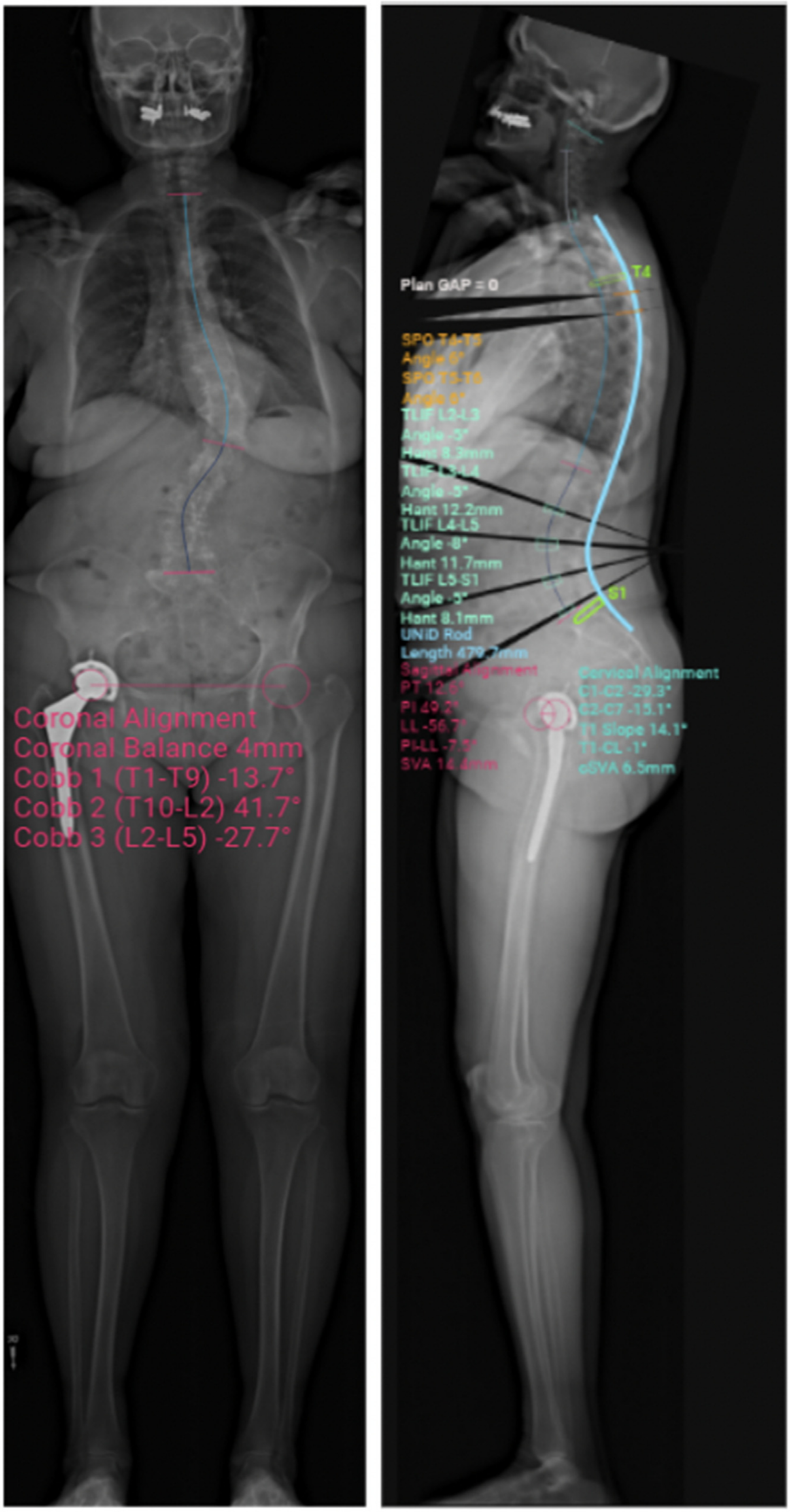
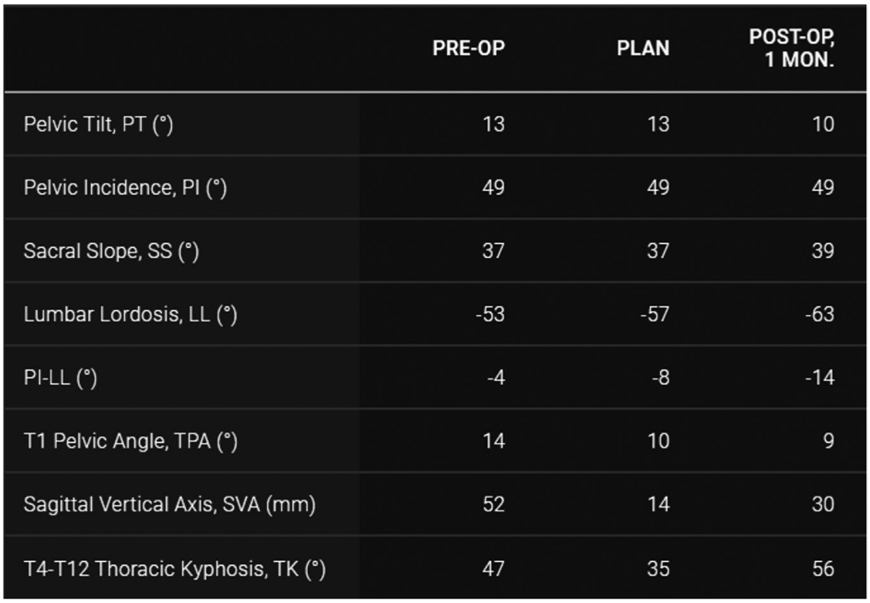


Fig. 7. Standing anteroposterior and lateral radiographs with overlaid surgical plan showing coronal and sagittal alignment goals including planned osteotomies, rod contouring, and segmental corrections.



	PRE-OP	PLAN	POST-OP, 1 MON.
Pelvic Tilt, PT (°)	13	13	10
Pelvic Incidence, PI (°)	49	49	49
Sacral Slope, SS (°)	37	37	39
Lumbar Lordosis, LL (°)	-53	-57	-63
PI-LL (°)	-4	-8	-14
T1 Pelvic Angle, TPA (°)	14	10	9
Sagittal Vertical Axis, SVA (mm)	52	14	30
T4-T12 Thoracic Kyphosis, TK (°)	47	35	56

Fig. 8. Comparison of preoperative, planned, and 1-month postoperative spinopelvic parameters.

failure [72–74]. In contrast, AI-enabled patient-specific rod systems, such as UNiD^{TM}, employ AI-based analysis of spinopelvic parameters to design patient-specific prebent rods. Yamada et al. [75] have demonstrated that these customized rods significantly reduce the incidence of instrumentation failure by aligning closely with targeted postoperative spinal geometries. Furthermore, Sadrameli et al. [76] reported no statistically significant differences between ideal alignment targets and achieved postoperative alignment when using patient-specific rods, indicating their effectiveness in replicating surgical goals with high fidelity. Lastly, Picton et al. [77], in a systematic review of 7 studies encompassing 304 ASD patients, observed consistent improvement trends across key alignment parameters including SVA, PI–LL, and pelvic tilt (PT). While these findings support the effectiveness of patient-specific rod systems, the authors also noted heterogeneity in surgical variables and patient characteristics, highlighting the need for continued refinement of predictive modeling techniques [76–78].

Beyond rod instrumentation, companies developing AI-based interbody implant systems, such as Carlsmed and others, are leveraging AI to create entirely patient-specific interbody devices. These implants are designed to conform precisely to the unique anatomical contours of a patient's vertebrae, based on detailed 3D imaging and AI-enabled segmentation. This design approach fosters a favorable environment for spinal fusion, enhancing biomechanical compatibility and potentially reducing the likelihood of pseudoarthrosis [79,80]. The use of such implants, including lateral lumbar interbody fusion (LLIF) and various transforaminal lumbar interbody fusion (TLIF) configurations, underscores the growing emphasis on personalization in achieving optimal long-term surgical outcomes.

Patient support and clinical workflow enhancement

The potential of AI in spine care extends beyond the operating room, particularly through the use of LLMs to enhance patient education and communication. In a 2024 study by Giakas et al. [81], ChatGPT was found to deliver broadly useful and comprehensible answers to common preoperative questions related to posterior lumbar decompression. The ability of AI to provide consistent, evidence-based responses may empower patients with a better understanding of their condition and improve informed consent processes. Yoseph et al. [82] evaluated LLM-generated responses to anterior cervical discectomy and fusion (ACDF) queries and found that, despite the small sample size, patient ratings for clarity and completeness were comparable to those of physician-generated responses. Notably, LLM responses were 80% shorter on average, suggesting improved efficiency without a sacrifice in quality. Although these study focused on nondeformity procedures, they illustrate the growing utility of LLMs in improving patient understanding and streamlining preoperative communication—an area that may be extended to deformity care.

In addition to patient communication, AI platforms are also being deployed to improve spine care delivery through digital health technologies. Companies like RevelAi Health have developed conversational AI tools and text-based support systems that offer real-time assistance for low back pain management. These platforms can triage symptoms, guide follow-up, and reduce clinician workload by automating routine inquiries and streamlining electronic communication [43,83]. By reducing call volume and enhancing inbox management, AI-enabled care orchestration systems improve clinician efficiency and address critical staffing shortages in spine clinics.

Taken together, these applications represent a paradigm shift in how AI is used not only to enhance intraoperative precision but also to deliver continuous, personalized, and scalable support across the patient care continuum. From customized implants and predictive surgical planning to AI-generated education and remote care tools, artificial intelligence is fundamentally transforming the way spine surgery is conceptualized, delivered, and experienced.

Case example

A 75-year-old female presented with a 5-year history of progressive back pain, which had markedly worsened over the past 3 years. The pain radiated bilaterally to the lower extremities, though she denied any bowel or bladder dysfunction. Her medical history was notable for asthma, gastroesophageal reflux disease (GERD), osteoporosis, and a history of uterine fibroids. Her surgical history included a total hysterectomy, right total hip arthroplasty with subsequent revision, and a left breast lumpectomy.

Prior conservative treatments including injections, physical therapy, nonsteroidal anti-inflammatory drugs (NSAIDs), and thermal therapy provided only minimal relief. On neurological examination, the patient exhibited bilateral lower extremity motor weakness, more pronounced

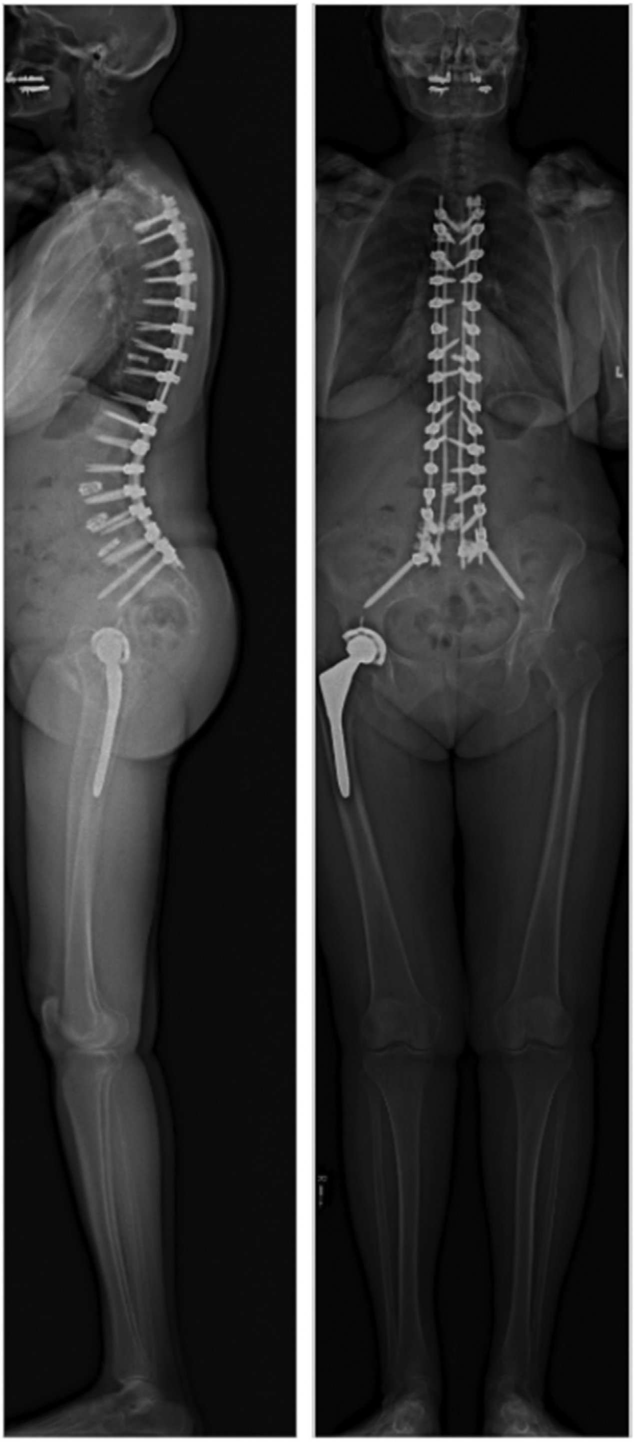


Fig. 9. Standing postoperative lateral and anteroposterior radiographs at 1 month demonstrating stable instrumentation and improved global spinal alignment following T4–S1 fusion with pelvic fixation.

on the left side, along with a diminished left L4 reflex (1+). Radiographic evaluation revealed thoracolumbar scoliosis, mild lumbar lordosis, thoracic kyphosis, and advanced multilevel degenerative changes. The most significant findings were at L5–S1, where imaging demonstrated severe disc space narrowing, endplate sclerosis, and prominent osteophytosis, consistent with advanced degenerative disc disease and foraminal stenosis contributing to her clinical symptoms. Preoperative spinopelvic measurements indicated abnormal global alignment. The patient had a pelvic tilt (PT) of 13°, pelvic incidence (PI) of 49°, sacral slope (SS) of 37°, and lumbar lordosis (LL) of −53°, resulting in a PI–LL mismatch of −4°. The sagittal vertical axis (SVA) was measured at 52 mm, and thoracic kyphosis (T4–T12) was 47°. These parameters reflected a compensated sagittal deformity with a moderate mismatch between the patient's lumbar curvature and pelvic anatomy (Fig. 5).

The surgical plan incorporated AI-guided preoperative planning using the UNiD^{TM} Adaptive Spine Intelligence platform (Medicrea/SpineGuard), which analyzed patient-specific spinopelvic parameters to generate alignment targets and precontoured rod specifications tailored to the patient's anatomy. The patient underwent a multilevel procedure including transforaminal lumbar interbody fusion (TLIF) from L2 to S1, posterior spinal fusion from T4 to S1, laminectomy, osteotomy, and pelvic fixation with fluoroscopic guidance. The AI-generated alignment targets included a modest improvement in LL to −57°, with a planned reduction in PI–LL mismatch to −8°, and a projected reduction in SVA from 52 mm to 14 mm (Figs. 6 and 7).

At 6-month follow-up, no intraoperative or postoperative complications were reported. Postoperative radiographic assessment, at 1-month, demonstrated that the patient achieved ideal alignment based on multiple classification systems, including GAP, Roussouly, and age-adjusted thresholds. Notably, the patient achieved a final LL of −63°, PI–LL mismatch of −14°, PT of 10°, and SVA of 30 mm. The thoracic kyphosis increased postoperatively to 56°, consistent with global compensatory changes (Figs. 8 and 9).

This case highlights the successful use of AI-assisted planning in achieving radiographic goals and avoiding complications in a complex adult spinal deformity patient. The alignment targets were not only met but exceeded in some parameters, and the clinical outcome was favorable without additional risk. This is why AI-based models should be used as a decision-support tool, rather than a definitive predictor or surgical outcome. These technologies are intended to augment, not replace, surgical judgement, by reducing planning burden and enhancing standardization while allowing for intraoperative adaptability.

Conclusion

Artificial intelligence has begun to redefine how ASD is studied, diagnosed, planned, and treated. From automating evidence synthesis to guiding intraoperative execution and enabling implant personalization, AI is enhancing precision, efficiency, and patient outcomes across every stage of the surgical workflow. While certain challenges around AI and its implementation remain, the trajectory is clear. AI is transitioning from a supplementary tool to an indispensable component of spine care.

The optimal future lies in a hybrid model that leverages the strengths of both human expertise and AI-driven computation. By fostering ongoing collaboration between data scientists, clinicians, and industry, the field can continue to evolve toward a more personalized, value-based, and outcomes-driven approach to spinal deformity surgery. With thoughtful implementation and rigorous validation, AI holds the potential to not only augment surgeon capabilities, but to elevate the standard of care for patients worldwide.

Funding

No funding was received for this study.

Data access statement

N/A.

Ethical review committee statement

N/A.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Joshi RS, Lau D, Ames CP. Artificial intelligence for adult spinal deformity: current state and future directions. Spine J 2021;21(10):1626–34. doi:10.1016/j.spinee.2021.04.019.
[2] Patel RV, Yearley AG, Isaac H, Chalif EJ, Chalif JI, Zaidi HA. Advances and evolving challenges in spinal deformity surgery. J Clin Med. 2023;12(19). doi:10.3390/jcm12196386.
[3] Wang D, Wang Q, Cui P, et al. Machine-learning models for the prediction of ideal surgical outcomes in patients with adult spinal deformity. Bone Joint J. 2025;107-b(3):337–45. doi:10.1302/0301-620x.107b3.Bjj-2024-1220.R1.
[4] Bcharah G, Gupta N, Panico N, et al. Innovations in spine surgery: a narrative review of current integrative technologies. World Neurosurg 2024;184:127–36. doi:10.1016/j.wneu.2023.12.124.
[5] Walker CT, Babadjouni R, Gibbs W, et al. Current concepts on imaging and artificial intelligence of osteosarcopenia in the aging spine: a review for Spinal surgeons by the SRS Adult Spinal Deformity Task Force on Senescence. Spine (Phila Pa 1976) 2025. doi:10.1097/brs.0000000000005426.
[6] Lu VM, Graffeo CS, Mikula AL, et al. Making the most of systematic reviews and meta-analyses in spine surgery: a primer for the practicing spine surgeon. Spine (Phila Pa 1976) 2020;45(13):E808–12. doi:10.1097/brs.0000000000003429.
[7] Bello A, Vandermeer B, Wiebe N, Garg AX, Tonelli M. Evidence-based decision-making 2: systematic reviews and meta-analysis. Methods Mol Biol 2021;2249:405–28. doi:10.1007/978-1-0716-1138-8_22.
[8] Créquit P, Boutron I, Meerpohl J, Williams HC, Craig J, Ravaud P. Future of evidence ecosystem series: 2. current opportunities and need for better tools and methods. J Clin Epidemiol 2020;123:143–52. doi:10.1016/j.jclinepi.2020.01.023.
[9] Boutron I, Créquit P, Williams H, Meerpohl J, Craig JC, Ravaud P. Future of evidence ecosystem series: 1. Introduction evidence synthesis ecosystem needs dramatic change. J Clin Epidemiol 2020;123:135–42. doi:10.1016/j.jclinepi.2020.01.024.
[10] Abogunrin S, Muir JM, Zerbini C, Sarri G. How much can we save by applying artificial intelligence in evidence synthesis? Results from a pragmatic review to quantify workload efficiencies and cost savings. Front Pharmacol 2025;16:1454245. doi:10.3389/fphar.2025.1454245.
[11] van Dijk SHB, Brusse-Keizer MGJ, Bucsán CC, van der Palen J, Doggen CJM, Lenferink A. Artificial intelligence in systematic reviews: promising when appropriately used. BMJ Open 2023;13(7):e072254. doi:10.1136/bmjopen-2023-072254.
[12] Yao X, Kumar MV, Su E, Flores Miranda A, Saha A, Sussman J. Evaluating the efficacy of artificial intelligence tools for the automation of systematic reviews in cancer research: a systematic review. Cancer Epidemiol 2024;88:102511. doi:10.1016/j.canep.2023.102511.
[13] Khalil H, Ameen D, Zarnegar A. Tools to support the automation of systematic reviews: a scoping review. J Clin Epidemiol 2022;144:22–42. doi:10.1016/j.jclinepi.2021.12.005.
[14] Michelson M, Chow T, Martin NA, Ross M, Tee Qiao Ying A, Minton S. Artificial intelligence for rapid Meta-analysis: case study on ocular toxicity of hydroxychloroquine. J Med Internet Res. 2020;22(8):e20007. doi:10.2196/20007.
[15] Tercero-Hidalgo JR, Khan KS, Bueno-Cavanillas A, et al. Artificial intelligence in COVID-19 evidence syntheses was underutilized, but impactful: a methodological study. J Clin Epidemiol 2022;148:124–34. doi:10.1016/j.jclinepi.2022.04.027.
[16] Lieberum JL, Toews M, Metzendorf MI, et al. Large language models for conducting systematic reviews: on the rise, but not yet ready for use-a scoping review. J Clin Epidemiol 2025;181:111746. doi:10.1016/j.jclinepi.2025.111746.
[17] Bernard N, Sagawa Y Jr, Bier N, Lihoreau T, Pazart L, Tannou T. Using artificial intelligence for systematic review: the example of elicit. BMC Med Res Methodol 2025;25(1):75. doi:10.1186/s12874-025-02528-y.
[18] Ge L, Agrawal R, Singer M, et al. Leveraging artificial intelligence to enhance systematic reviews in health research: advanced tools and challenges. Syst Rev 2024;13(1):269. doi:10.1186/s13643-024-02682-2.
[19] Woelfle T, Hirt J, Janiaud P, Kappos L, Ioannidis JPA, Hemkens LG. Benchmarking Human-AI collaboration for common evidence appraisal tools. J Clin Epidemiol 2024;175:111533. doi:10.1016/j.jclinepi.2024.111533.
[20] Joshi RS, Haddad AF, Lau D, Ames CP. Artificial intelligence for adult spinal deformity. Neurospine 2019;16(4):686–94. doi:10.14245/ns.1938414.207.
[21] Joshi RS, Lau D, Scheer JK, et al. State-of-the-art reviews predictive modeling in adult spinal deformity: applications of advanced analytics. Spine Deform 2021;9(5):1223–39. doi:10.1007/s43390-021-00360-0.
[22] Wondra JP 2nd, Kelly MP, Greenberg J, et al. Validation of adult spinal deformity surgical outcome prediction tools in adult symptomatic lumbar scoliosis. Spine (Phila Pa 1976) 2023;48(1):21–8. doi:10.1097/brs.0000000000004416.
[23] Scheer JK, Osorio JA, Smith JS, et al. Development of a preoperative predictive model for reaching the Oswestry disability index minimal clinically important difference for adult spinal deformity patients. Spine Deform 2018;6(5):593–9. doi:10.1016/j.jspd.2018.02.010.
[24] Pellisé F, Serra-Burriel M, Smith JS, et al. Development and validation of risk stratification models for adult spinal deformity surgery. J Neurosurg Spine 2019;31(4):587–99. doi:10.3171/2019.3.Spine181452.
[25] Safaee MM, Scheer JK, Ailon T, et al. Predictive modeling of length of hospital stay following adult spinal deformity correction: analysis of 653 patients with an accuracy of 75% within 2 days. World Neurosurg 2018;115:e422–7. doi:10.1016/j.wneu.2018.04.064.
[26] Charles YP, Lamas V, Ntilikina Y. Artificial intelligence and treatment algorithms in spine surgery. Orthop Traumatol Surg Res. 2023;109(1s):103456. doi:10.1016/j.otsr.2022.103456.
[27] Ames CP, Smith JS, Pellisé F, et al. Artificial intelligence based hierarchical clustering of patient types and intervention categories in adult spinal deformity surgery: towards a new classification scheme that predicts quality and value. Spine (Phila Pa 1976) 2019;44(13):915–26. doi:10.1097/brs.0000000000002974.
[28] Baroncini A, Boissiere L, Larrieu D, et al. Comparison of patients with and without predicted surgical indication between clusters of adult spine deformity (ASD) patients. Spine (Phila Pa 1976) 2025;50(14):975–80. doi:10.1097/brs.0000000000005173.
[29] Hornung AL, Hornung CM, Mallow GM, et al. Artificial intelligence in spine care: current applications and future utility. Eur Spine J. 2022;31(8):2057–81. doi:10.1007/s00586-022-07176-0.
[30] Ames CP, Smith JS, Gum JL, et al. Utilization of predictive modeling to determine episode of care costs and to accurately identify catastrophic cost nonwarranty outlier patients in adult spinal deformity surgery: a step toward bundled payments and risk sharing. Spine (Phila Pa 1976) 2020;45(5):E252–65. doi:10.1097/brs.0000000000003242.
[31] Ames CP, Smith JS, Pellisé F, et al. Development of deployable predictive models for minimal clinically important difference achievement across the commonly used health-related quality of life instruments in adult spinal deformity surgery. Spine (Phila Pa 1976) 2019;44(16):1144–53. doi:10.1097/brs.0000000000003031.
[32] Oh T, Scheer JK, Smith JS, et al. Potential of predictive computer models for preoperative patient selection to enhance overall quality-adjusted life years gained at 2-year follow-up: a simulation in 234 patients with adult spinal deformity. Neurosurg Focus. 2017;43(6):E2. doi:10.3171/2017.9.Focus17494.
[33] Sardjono TA, Wilkinson MH, Veldhuizen AG, van Ooijen PM, Purnama KE, Verkerke GJ. Automatic Cobb angle determination from radiographic images. Spine (Phila Pa 1976) 2013;38(20):E1256–62. doi:10.1097/BRS.0b013e3182a0c7c3.
[34] Schwartz JT, Cho BH, Tang P, et al. Deep learning automates measurement of spinopelvic parameters on lateral lumbar radiographs. Spine (Phila Pa 1976) 2021;46(12):E671–8. doi:10.1097/brs.0000000000003830.
[35] Harake ES, Linzey JR, Jiang C, et al. Development and validation of an artificial intelligence model to accurately predict spinopelvic parameters. J Neurosurg Spine 2024;41(1):88–96. doi:10.3171/2024.1.Spine231252.
[36] Joshi RS, Harake ES, Jiang C, et al. Validation of a novel artificial intelligence model (SpinePose) to automatically and accurately predict spinopelvic parameters using scoliosis radiographs in an external cohort. Neurosurg Focus 2025;58(6):E10. doi:10.3171/2025.3.Focus2574.
[37] Grover P, Siebenwirth J, Caspari C, et al. Can artificial intelligence support or even replace physicians in measuring sagittal balance? A validation study on preoperative and postoperative full spine images of 170 patients. Eur Spine J. 2022;31(8):1943–51. doi:10.1007/s00586-022-07309-5.
[38] Kang DH, Jeong YJ, Kim ST, et al. Automated measurement of pelvic parameters using convolutional neural network in complex spinal deformities: overcoming challenges in coronal deformity cases. Spine J. 2025. doi:10.1016/j.spinee.2025.01.020.
[39] Landriel F, Franchi BC, Mosquera C, et al. Artificial intelligence assistance for the measurement of full alignment parameters in whole-spine lateral radiographs. World Neurosurg 2024;187:e363–82. doi:10.1016/j.wneu.2024.04.091.
[40] Yeh YC, Weng CH, Huang YJ, Fu CJ, Tsai TT, Yeh CY. Deep learning approach for automatic landmark detection and alignment analysis in whole-spine lateral radiographs. Sci Rep 2021;11(1):7618. doi:10.1038/s41598-021-87141-x.
[41] Lafage R, Ang B, Alshabab BS, et al. Predictive model for selection of upper treated vertebra using a machine learning approach. World Neurosurg 2021;146:e225–32. doi:10.1016/j.wneu.2020.10.073.
[42] Peng L, Lan L, Xiu P, et al. Prediction of proximal junctional kyphosis after posterior scoliosis surgery with machine learning in the Lenke 5 adolescent idiopathic scoliosis patient. Front Bioeng Biotechnol 2020;8:559387. doi:10.3389/fbioe.2020.559387.
[43] Yagi M, Yamanouchi K, Fujita N, Funao H, Ebata S. Revolutionizing spinal care: current applications and future directions of Artificial intelligence and machine learning. J Clin Med 2023;12(13). doi:10.3390/jcm12134188.
[44] Loftus TJ, Altieri MS, Balch JA, et al. Artificial intelligence-enabled decision support in surgery: state-of-the-art and Future directions. Ann Surg 2023;278(1):51–8. doi:10.1097/sla.0000000000005853.
[45] Lawson McLean A. Towards precision medicine in spinal surgery: leveraging AI technologies. Ann Biomed Eng 2024;52(4):735–7. doi:10.1007/s10439-023-03315-w.
[46] Adida S, Legarreta AD, Hudson JS, et al. Machine learning in spine surgery: a narrative review. Neurosurgery 2024;94(1):53–64. doi:10.1227/neu.0000000000002660.
[47] Koller H, Hitzl W, Marks MC, Newton PO. Accurate prediction of spontaneous lumbar curve correction following posterior selective thoracic fusion in adolescent idiopathic scoliosis using logistic regression models and clinical rationale. Eur Spine J 2019;28(9):1987–97. doi:10.1007/s00586-019-06000-6.
[48] Phan P, Mezghani N, Wai EK, de Guise J, Labelle H. Artificial neural networks assessing adolescent idiopathic scoliosis: comparison with Lenke classification. Spine J. 2013;13(11):1527–33. doi:10.1016/j.spinee.2013.07.449.
[49] Perfetti DC, Kisinde S, Rogers-LaVanne MP, Satin AM, Lieberman IH. Robotic spine surgery: past, present, and future. Spine (Phila Pa 1976) 2022;47(13):909–21. doi:10.1097/brs.0000000000004357.

[50] Davidar AD, Jiang K, Weber-Levine C, Bhimreddy M, Theodore N. Advancements in robotic-assisted spine surgery. Neurosurg Clin N Am 2024;35(2):263–72. doi:10.1016/j.nec.2023.11.005.

[51] Koucheki R, Bonello JP, Abbas A, et al. A comparison of key performance metrics of major robotic platforms in spine surgery: a network meta-analysis of 14,462 screws. Eur Spine J. 2025. doi:10.1007/s00586-025-08990-y.

[52] Łajczak P, Żerdziński K, Jóźwik K, Laskowski M, Dymek M. Enhancing precision and safety in spinal surgery: a comprehensive review of robotic assistance technologies. World Neurosurg 2024;191:109–16. doi:10.1016/j.wneu.2024.08.051.

[53] Mao JZ, Agyei JO, Khan A, et al. Technologic evolution of navigation and robotics in spine surgery: a historical perspective. World Neurosurg 2021;145:159–67. doi:10.1016/j.wneu.2020.08.224.

[54] Zeng J, Fu Q. A review: artificial intelligence in image-guided spinal surgery. Expert Rev Med Dev 2024;21(8):689–700. doi:10.1080/17434440.2024.2384541.

[55] Khan A, Meyers JE, Yavorek S, et al. Comparing next-generation robotic technology with 3-dimensional computed tomography navigation technology for the insertion of posterior pedicle screws. World Neurosurg 2019;123:e474–81. doi:10.1016/j.wneu.2018.11.190.

[56] Liebmann F, von Atzigen M, Stütz D, et al. Automatic registration with continuous pose updates for marker-less surgical navigation in spine surgery. Med Image Anal 2024;91:103027. doi:10.1016/j.media.2023.103027.

[57] Wandvik C, Greil ME, Colby S, Gautam D, Mazur MD. Limitations of current robot-assisted pedicle screw insertion systems. Neurosurg Focus 2024;57(6):E14. doi:10.3171/2024.9.Focus24545.

[58] Loggia G, Altorfer FCS, Avrumova F, Lebl DR. Identification of potential pitfalls and complication avoidance in robotic-assisted spine surgery. J Am Acad Orthop Surg. 2025. doi:10.5435/jaaos-D-25-00031.

[59] Jecklin S, Jancik C, Farshad M, Fürnstahl P, Esfandiari H. X23D-Intraoperative 3D lumbar spine shape reconstruction based on sparse multi-view X-ray data. J Imaging 2022;8(10). doi:10.3390/jimaging8100271.

[60] Farber SH, Pacult MA, Godzik J, et al. Robotics in spine surgery: a technical overview and review of key concepts. Front Surg 2021;8:578674. doi:10.3389/fsurg.2021.578674.

[61] MacLean L, Hersh AM, Bhimreddy M, et al. Comparison of accuracy, revision, and perioperative outcomes in robot-assisted spine surgeries: systematic review and meta-analysis. J Neurosurg Spine 2024;41(4):519–31. doi:10.3171/2024.4.Spine23917.

[62] Huang M, Tetreault TA, Vaishnav A, York PJ, Staub BN. The current state of navigation in robotic spine surgery. Ann Transl Med 2021;9(1):86. doi:10.21037/atm-2020-ioi-07.

[63] Wilson BR, Wang TY, O'Toole J. Augmented reality in spine surgery. Neurosurgery 2025;96(3s):S103–10. doi:10.1227/neu.0000000000003343.

[64] Pierzchajlo N, Stevenson TC, Huynh H, et al. Augmented reality in minimally invasive spinal surgery: a narrative review of available technology. World Neurosurg 2023;176:35–42. doi:10.1016/j.wneu.2023.04.030.

[65] Shi J, Hou Y, Lin Y, Chen H, Yuan W. Role of visuohaptic surgical training simulator in resident education of orthopedic surgery. World Neurosurg 2018;111:e98–e104. doi:10.1016/j.wneu.2017.12.015.

[66] Gottschalk MB, Yoon ST, Park DK, Rhee JM, Mitchell PM. Surgical training using three-dimensional simulation in placement of cervical lateral mass screws: a blinded randomized control trial. Spine J 2015;15(1):168–75. doi:10.1016/j.spinee.2014.08.444.

[67] Li T, Yan J, Gao X, et al. Using virtual reality to enhance surgical skills and engagement in orthopedic education: systematic review and meta-analysis. J Med Internet Res 2025;27:e70266. doi:10.2196/70266.

[68] Mao RQ, Lan L, Kay J, et al. Immersive Virtual reality for surgical training: a systematic review. J Surg Res 2021;268:40–58. doi:10.1016/j.jss.2021.06.045.

[69] Zaki MM, Joshi RS, Joseph JR, et al. Virtual reality-enabled resident education of lateral-access spine surgery. World Neurosurg 2024;183:e401–7. doi:10.1016/j.wneu.2023.12.108.

[70] Laskay NMB, George JA, Knowlin L, Chang TP, Johnston JM, Godzik J. Optimizing surgical performance using preoperative virtual reality planning: a systematic review. World J Surg 2023;47(10):2367–77. doi:10.1007/s00268-023-07064-8.

[71] Lyuksemburg V, Abou-Hanna J, Marshall JS, et al. Virtual reality for preoperative planning in complex surgical oncology: a single-center experience. J Surg Res. 2023;291:546–56. doi:10.1016/j.jss.2023.07.001.

[72] Antes S, Moringlane R, von Eckardstein KL. Augmented reality-supported rod bending in multilevel spinal fusion using the ADVISE software. World Neurosurg 2023;178:96–100. doi:10.1016/j.wneu.2023.07.029.

[73] Sudo H, Tachi H, Kokabu T, et al. In vivo deformation of anatomically pre-bent rods in thoracic adolescent idiopathic scoliosis. Sci Rep 2021;11(1):12622. doi:10.1038/s41598-021-92187-y.

[74] Miri O, Amellal O, Detrembleur C, Troussel S, Vandergugten S. Sagittal alignment correction of adolescent idiopathic scoliosis using patient-specific rods. Eur Spine J. 2025. doi:10.1007/s00586-025-08768-2.

[75] Yamada K, Sudo H, Iwasaki N, Chiba A. Mechanical analysis of notch-free pre-bent rods for spinal deformity surgery. Spine (Phila Pa 1976) 2020;45(6):E312–18. doi:10.1097/brs.0000000000003269.

[76] Sadrameli SS, Boghani Z, Steele Iii WJ, Holman PJ. Utility of patient-specific rod instrumentation in deformity correction: single institution experience. Spine Surg Relat Res 2020;4(3):256–60. doi:10.22603/ssrr.2019-0101.

[77] Picton B, Stone LE, Liang J, et al. Patient-specific rods in adult spinal deformity: a systematic review. Spine Deform 2024;12(3):577–85. doi:10.1007/s43390-023-00805-8.

[78] Kleck CJ, Calabrese D, Reeves BJ, et al. Long-term treatment effect and predictability of spinopelvic alignment after surgical correction of adult spine deformity with patient-specific spine rods. Spine (Phila Pa 1976) 2020;45(7):E387–96. doi:10.1097/brs.0000000000003290.

[79] Smit T, Aage N, Haschtmann D, Ferguson SJ, Helgason B. In silico medical device testing of anatomically and mechanically conforming patient-specific spinal fusion cages designed by full-scale topology optimisation. Front Bioeng Biotechnol 2024;12:1347961. doi:10.3389/fbioe.2024.1347961.

[80] Sattari SA, Xia Y, Azad TD, Caraway CA, Chang L. Advances in implant technologies for spine surgery. Neurosurg Clin N Am 2024;35(2):217–27. doi:10.1016/j.nec.2023.11.003.

[81] Giakas AG, Narayanan R, Ezeonu T, et al. Assessing the accuracy and utility of ChatGPT responses to patient questions regarding posterior lumbar decompression. Artific Intell Surg 2024;4(2771–0408):233–46. doi:10.20517/ais.2024.24.

[82] Yoseph ET, Gonzalez-Suarez AD, Lang S, Desai A, Hu SS, Zygourakis CC. Patient perspectives on AI: a pilot study comparing large language model and physician-generated responses to routine cervical spine surgery questions. Artific Intell Surg 2024;4(2771–0408):267–77. doi:10.20517/ais.2024.38.

[83] Simpson AK, Crawford AM, Striano BM, Kang JD, Schoenfeld AJ. The future of spine care innovation-software not hardware: how the digital transformation will change spine care delivery. Spine (Phila Pa 1976) 2023;48(1):73–8. doi:10.1097/brs.0000000000004487.