Review

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Application of artificial intelligence in diagnosis and treatment of spinal deformities

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Abstract:

Spinal deformity is a relatively common and serious disease. Due to the complexity of the disease and the risk of treatment, it is important to develop effective assessment, screening, treatment, and prediction tools. As a new type of productivity, the application of artificial intelligence (AI) in the medical field is expanding and deepening, bringing revolutionary changes to clinical work. AI has changed the whole process of spinal deformity from early evaluation and screening to surgical decision-making and assistance by improving diagnostic accuracy, work efficiency, and personalized diagnosis and treatment. Through automated standardized imaging parameter measurements, AI has significantly enhanced diagnostic efficiency and consistency. Combined with cluster analysis and multimodal data, AI has strengthened the objectivity and scientific rigor of spinal deformity classification. Moreover, AI's potential in surgical planning and risk prediction is increasingly evident, driving the development of personalized treatment. AI-integrated robotic navigation systems not only improve surgical outcomes but also accelerate physicians' professional growth. However, key bottlenecks in clinical AI applications remain data universality, algorithmic interpretability, and ethical regulatory constraints. Future research should focus on high-quality, multicenter, long-term clinical validation studies to provide robust evidence for AI's effectiveness and safety. Accelerating the development of explainable AI will help demystify decision-making processes and build clinical trust. Improving regulatory frameworks and standardized supervision mechanisms is crucial for delivering tangible patient benefits. AI's vast potential lies in ushering spinal deformity management into a new era of precision medicine and data-driven approaches, becoming an indispensable force in spinal deformity prevention and treatment.

Abbreviations: 2D = two dimensional, 3D = three dimensional, AI = artificial intelligence, AIS = adolescent idiopathic scoliosis, AR = augmented reality, ASD = adult spinal deformities, AUC = area under the curve, CNN = convolutional neural networks, DL = deep learning, ICC = intraclass correlation coefficient, LL = lumbar lordosis, LLM = large language model, LLNet = localization network, ML = machine learning, ODI = Oswestry disability index, PJF = proximal junctional failure, PJK = proximal junctional kyphosis, SVA = sagittal vertical axis, TK = thoracic kyphosis, VR = virtual reality.

Keywords: artificial intelligence, diagnosis, evaluation, prediction, spinal deformities, treatment

1. Introduction

Spinal deformities refer to abnormal anatomical deviations in the spine's coronal, sagittal, or axial planes, manifesting as morphological abnormalities such as scoliosis, abnormal kyphosis or lordosis, and vertebral rotation. These conditions often present with physical deformities, pain, and neurological impairments. Severe cases may compromise cardiopulmonary function, causing breathing difficulties that can be life-threatening. Such deformities pose significant public health risks while imposing substantial medical and economic burdens on both individuals and society.[1] Early screening, accurate diagnosis, and scientific intervention are key to controlling the progression of spinal deformities, avoiding serious complications and improving prognosis.[2] However, the evaluation and treatment of spinal deformities involve complex biomechanical and anatomical considerations, and their complexity and diversity pose many challenges for clinical diagnosis and treatment.

Artificial intelligence (AI), as a powerful tool for liberating and enhancing productivity, is gaining widespread attention and application. Its core lies in simulating human intelligence through computer systems, encompassing capabilities such as learning, reasoning, problem-solving, perception, and language comprehension.[3] Currently, AI has been extensively applied in medicine. Leveraging its

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formidable data processing and pattern recognition abilities, AI provides revolutionary tools for disease diagnosis and screening, as well as treatment plan optimization.

In recent years, AI, particularly machine learning (ML) and deep learning (DL), has demonstrated significant clinical potential across various aspects of spinal deformity diagnosis and treatment. AI can automatically learn complex patterns and features from medical data, enabling rapid, accurate, and standardized evaluation and processing of spinal parameters.[4] This significantly enhances diagnostic accuracy, treatment safety, and scientific decision-making.[5,6] Based on existing research evidence, this review systematically examines the current clinical applications of AI in spinal deformity management while exploring its challenges and future development directions.

2. Application of AI in analysis and diagnosis of spinal deformities

2.1. Image automation measurement and parameters extraction

The diagnosis, treatment, and prognosis assessment of spinal deformities rely on accurate interpretation of spinal imaging. Traditionally, physicians manually measure key radiological parameters such as Cobb angle, sagittal vertical axis (SVA), and pelvic tilt (PT) to evaluate deformity severity, formulate treatment plans, and monitor disease progression.[7] This process is not only time-consuming and laborious, but also has significant differences between observers and within observers. The measurement error can reach 5° to 10°, and there are limitations such as low efficiency, strong subjectivity and poor repeatability, which directly affect the consistency and accuracy of clinical decisions.[8,9]

The application of AI in spinal imaging evaluation has significantly improved this issue, enhancing both efficiency and reliability. DL algorithms such as convolutional neural networks (CNN)-based U-Net and its variants (including Residual U-Net and Dense U-Net), along with Deeplab V3+, are employed for model training. These models, through extensive learning from annotated spinal radiological images, can automatically perform processes like image segmentation, identification and localization of anatomical landmarks, and calculation of key spinal-hip parameters.[10–12]

Multiple studies have confirmed the superior performance of AI in automated measurement. CNN is a DL model specifically designed to process grid-topology data (e.g., images) to automatically extract spatially hierarchical features from raw pixels by mimicking the working mechanism of the biological visual cortex.[13] A complete CNN with anatomical identification accuracy of 93% performed both iterative instance segmentation and recognition of vertebrae by Lessmann et al., but lacked image datasets for cervical vertebrae and spinal implants.[14] Cho et al. used computer vision algorithms to automatically calculate the lumbar lordosis (LL), finding that compared with the manual measurement results, the algorithm achieves an average absolute error of 8.055° and a median absolute error of 6.965°, which has no statistical significance.[15] Payer et al. proposed a CNN architecture that learns to decompose anatomical landmark localization tasks into two simpler subproblems, thereby reducing the overall demand for large training datasets, which achieved advanced results in landmark localization error across various two-dimensional (2D) and three-dimensional (3D) datasets, even with limited available training images.[16] Berlin et al. developed an AI algorithm that can automatically detect the anatomy of adolescent idiopathic scoliosis (AIS) patients. In the evaluation of coronal parameters of the whole spine image before surgery, the AI algorithm showed a high degree of reliability consistent with human raters.[17] The SpinePose AI model has been shown to accurately predict spinal-pelvic parameters and is applicable to external sequences independent of model training and validation.[18] Furthermore, large language models (LLMs) with advanced pattern recognition capabilities significantly improve the classification accuracy and precision for complex spinal disorders by employing a multimodal DL approach that combines magnetic resonance imaging (MRI) features extracted via CNN with numerical spinal measurements.[19]

The Cobb angle is the "gold standard" for assessing the severity of scoliosis deformity, and its accurate measurement is crucial. Currently, AI is the most mature and widely used in this field. A CNN-based DL architecture for spinal segmentation and vertebral detection, which can calculate the Cobb angle of AIS by indirect calculation of vertebral positioning with a high accuracy of 93.6%.[20] Li et al. developed a new AI mobile application (cobbAngle pro) to automatically detect Cobb angles in patients with scoliosis, and demonstrated accurate and repeatable detection results.[21] The mean absolute difference of the AI model for automated measurement using polynomial fitting combined with sufficient image training was typically less than 5°, which is considered an acceptable error range in clinical practice compared with manual measurement by a physician.[22] In terms of consistency, the intraclass correlation coefficient (ICC) measured by AI was generally higher than 0.950, which was significantly better than manual measurement (the ICC of manual measurement was about 0.926), effectively solving the problem of observer variability in manual measurement.[23,24] Computer-aided method also has good reliability for Cobb angle measurement of chest X-ray. Pan et al. used the manual measurement of Cobb angle mean > 10° as a reference standard for scoliosis and found that the computer aided method had high sensitivity (89.59%) and relatively low specificity (70.37%) in the diagnosis of scoliosis on chest X-ray.[25] Zhang et al. proposed an effective framework named MPF-net (multi-task, proposal correlation, and feature fusion), which can detect blurred vertebrae obscured by arms and enhance performance by leveraging information between anteroposterior and lateral X-rays, achieving more precise vertebrae detection

and landmark prediction.[26] However, more abnormal images are expected to be incorporated into the datasets to enhance the performance boundaries of the models and more direct human–machine feedback patterns are anticipated to be developed to improve the operational efficiency and practicality of the models.

In addition to the Cobb angle in the coronal plane, the application of AI has been extended to a series of complex parameters such as thoracic kyphosis (TK), LL, and sacral slope for automatic measurement.[27,28] Meng et al. developed and prospectively validated a hybrid model, SpineHRNet+, which integrates AI with rule-based methods. The model demonstrated an average angular error of 6.32° between predicted sagittal spine parameters and manual measurements, with all predicted alignments showing strong correlations with manual measurements ($p < 0.001$, $R^2 > 0.97$). This significantly enhances the reliability and interpretability of automated alignment.[29] Harake et al. proposed a novel ML-based AI tool called SpinePose to automatically measure spinal-pelvic parameters with a median error range of 0.1° to 1.4°, demonstrating excellent reliability (ICC 0.910–1.000) and enabling standardization of clinical evaluation.[30]

The work efficiency advantage of AI is also significant. A pipeline using the SpineTK architecture was trained, validated, and tested to automatically measure the Cobb angle of suspected scoliosis. The algorithm can complete the measurement in 0.5 s and the results are not significantly different from the ground truth measurements.[31] An AI system using CNN measured one patient's Cobb angle and the Lenke classification in just 0.2 s, compared with 23.6 min for a surgeon.[32] Leveraging ResUNet's capability to enhance precision and efficiency in medical image segmentation through residual connections and multiscale feature fusion, Weng et al.'s automated method achieved SVA measurement from a lateral radiograph of whole spine within approximately 0.2 s with excellent consistency.[33]

This order-of-magnitude efficiency improvement provides a revolutionary solution for efficient, accurate, and automated screening of spinal deformities. Traditional screening methods rely on manual observation and measurement, which are limited by high subjectivity, low efficiency, high costs, and heavy dependence on specialists. These limitations compromise diagnostic consistency and hinder the formulation of an appropriate treatment plan.[34] Watanabe et al. created a scoliosis screening system that estimates spinal alignment, Cobb angle, and vertebral rotation from Moiré images.[35] The system demonstrates a mean absolute error of 3.6 pixels per individual in estimating vertebral positioning. And the mean absolute error between physicians' measured Cobb angles and the system's estimated values is 3.42°. By integrating AI models into screening workflows, we can achieve rapid, objective, and cost-effective screening of spinal deformities at large population scales. This approach liberates healthcare professionals from repetitive tasks, allowing them to focus on complex diagnostic and therapeutic decisions, thereby significantly enhancing the overall effectiveness of spinal deformity prevention and treatment. More importantly, by eliminating subjectivity, it improves measurement repeatability and reliability while ensuring comparability across different evaluations conducted by varying physicians at different times. This provides a robust data foundation for subsequent treatment planning, long-term disease monitoring, and evaluation of therapeutic outcomes.

2.2. 3D reconstruction and comprehensive evaluation

Traditional 2D imaging cannot fully reflect the complex spatial structure of spinal deformity, and the combination of AI and advanced imaging technology promotes the paradigm shift from 2D to 3D in spinal deformity evaluation.[36] By integrating multimodal recognition technologies, AI systems can assist in 3D spinal reconstruction, providing doctors with more intuitive and comprehensive structural information about deformities while overcoming the limitations of traditional 2D measurements. Combined with advanced imaging techniques like low-dose stereotactic X-ray, AI-powered modeling software enables 3D reconstruction and comprehensive evaluation of spinal deformities. Particularly effective in assessing axial plane deformities of AIS, this technology plays a crucial role in understanding pathological mechanisms and guiding surgical interventions for correction.[37]

In addition, AI is combined with radiation-free or low-radiation technologies such as ultrasound and rasterstereography to achieve quantitative assessment of spinal alignment and tissue structure, which is particularly suitable for large-scale early screening and longitudinal follow-up of AIS. Huang et al. proposed a localization network (LLNet) capable of automatically learning anatomical landmark-related positional information for the effective extraction of anatomical landmarks from 3D spinal ultrasound imaging, which is expected to be a useful part of a computer aided diagnosis system with a 100.0% detection success rate and an 8.9% improvement of mean intersection over the union.[38] Using a novel automated asymmetric assessment system with 3D depth sensors, Sudo et al. analyzed the human back surface to determine the severity of scoliosis. When predicting idiopathic scoliosis exceeding 25°, the system demonstrated an area under the curve (AUC) of 0.960, with a sensitivity of 0.97 and specificity of 0.88.[39] Mohamed et al. used 3D markerless surface topography technology to quantify trunk asymmetry, combined with the deviation data of back surface depth and torso surface depth, and developed a CNN model, which is expected to become a reliable noninvasive method for scoliosis screening.[40] However, since the procedures were performed by multiple investigators, intragroup and intergroup differences should be taken into account.

2.3. Spinal deformities typing and classification

To scientifically guide treatment decisions and evaluate patient prognosis, various spinal deformities classification systems have been developed in clinical practice. Among

them, the most famous are the Lenke classification and the King classification for AIS.[41,42] These classification systems mainly rely on the parameter measurement and morphological evaluation of imaging data such as X-ray films, which are highly dependent on doctors' professional knowledge and subjective judgment, and have low reliability within and between observers. The reliability of the King classification system has been shown to be relatively low, while the Lenke classification system's complex rules make its application time-consuming and error-prone. These limitations not only affect diagnostic consistency but also pose challenges for standardizing clinical research and treatment protocols. AI can automatically learn complex patterns and features from massive medical imaging data, enabling automated classification and categorization based on precise, rapid, and repeatable measurements of key parameters in spinal deformities. This advancement enhances diagnostic efficiency and accuracy while promoting standardized and intelligent management of spinal deformity diagnosis and treatment.

At present, the primary application goal of AI is to realize the automation of the traditional mature classification system to improve efficiency and reliability.[43] The Lenke classification plays a key role in determining the appropriate level of fusion for treatment plans. Lu et al. proposed an AI system showing high accuracy in Lenke classification, with high reliability compared with senior physicians (ICC 0.962).[32] One DL architecture named Landmark and Adjacent Offset Detection (LAD-Net), designed by Du et al., can predict spine center and corner points as well as their related offset vectors, calculate key parameters, and complete AIS Lenke diagnosis, but the algorithm may encounter challenges when dealing with extreme cases of severe deformities.[44] Scoliosis comes in two types of curvature (C or S). Tavanac found that the pretrained Xception and mobilenetV2 networks with the advantage of the balance of high computational efficiency and feature representation ability, which use support vector machine as the final activation function to control gradient disappearance, performed better than traditional ML methods in spinal curvature type classification tasks.[45] He et al. developed a system that can automatically classify cases of scoliosis secondary to neurofibromatosis type 1 with nondystrophic or dystrophic curves using DL algorithm with 80.36% accuracy.[46]

Furthermore, AI-driven algorithms such as unsupervised clustering have transcended conventional image analysis by identifying novel subtypes or phenotypes that were previously unclinically defined. These emerging classifications may better reflect patients' pathophysiological states and predict their responses to specific therapies compared with traditional categorizations, thereby opening new perspectives for both fundamental research and clinical practice in spinal deformities. Ames et al. produced a novel classification method for adult spinal deformities (ASD) using unsupervised AI-based hierarchical clustering technology.[47] This approach integrates key information such as demographic characteristics, weakness indicators, imaging data, and functional status of patients, ultimately forming a new ASD classification system comprising 12 subgroups, exhibiting significant differences in baseline parameters, treatment regimens, and rates of major complications.

Using ML algorithms to analyze prospective multicenter study data, Mohanty et al. identified four distinct qualitative phenotypes of ASD patients that were defined by their age frailty, physical functioning, and mental health upon presentation, and determined postoperative patient-reported outcomes.[48] Lafage et al. also used unsupervised clustering methods to classify patients into four clusters: hyper-TK, severe coronal, severe sagittal, and moderate sagittal to optimize treatment quality and safety.[49] These intelligent classifications go beyond traditional classification systems, enabling doctors to have a deeper understanding of the patient's "risk-benefit" portrait, so as to make more targeted treatment decisions for them and provide a stronger basis for personalized precision treatment (Fig. 1).

3. Application of AI in therapeutic decision and surgical planning of spinal deformities

3.1. Individualized prognosis assessment and risk prediction

Predicting treatment outcomes stands as a pivotal application of AI in medicine. ML models can integrate extensive preoperative variables—including demographic, imaging, and surgical factors—into training large retrospective databases to forecast various clinical outcomes. These predictions encompass improvements in patient-reported outcomes, postoperative complications, and reoperation risks.[50] By providing data-driven decision support for both physicians and patients, this approach facilitates the development of more personalized treatment plans.

The patient data can be analyzed by an ML model to predict whether the patient needs surgical treatment or nonsurgical treatment, and guide the timing of intervention. Durand et al. developed a support vector machine linear model that achieved 86% accuracy in predicting whether patients needed surgery.[51] The SRS-Schwab classification of ASD based on multiple health-related quality of life indicators reflected the severity of the disease state and was significantly associated with the decision to undergo surgical or nonsurgical treatment.[52] However, it is undeniable that current research lack a universally accepted standardized protocol for determining surgical versus nonsurgical decisions, with choices being made solely based on the clinical judgment and patient preferences, which highlights the urgent need for a standardized model to guide surgical decision-making in the future.

The AI models are also able to predict the degree of improvement in patients' postoperative function and quality of life. A ML model developed by Wang et al. for predicting ideal postoperative outcomes in individuals with ASD identified eight key prognostic variables: depression, osteoporosis, frailty, failure of pelvic

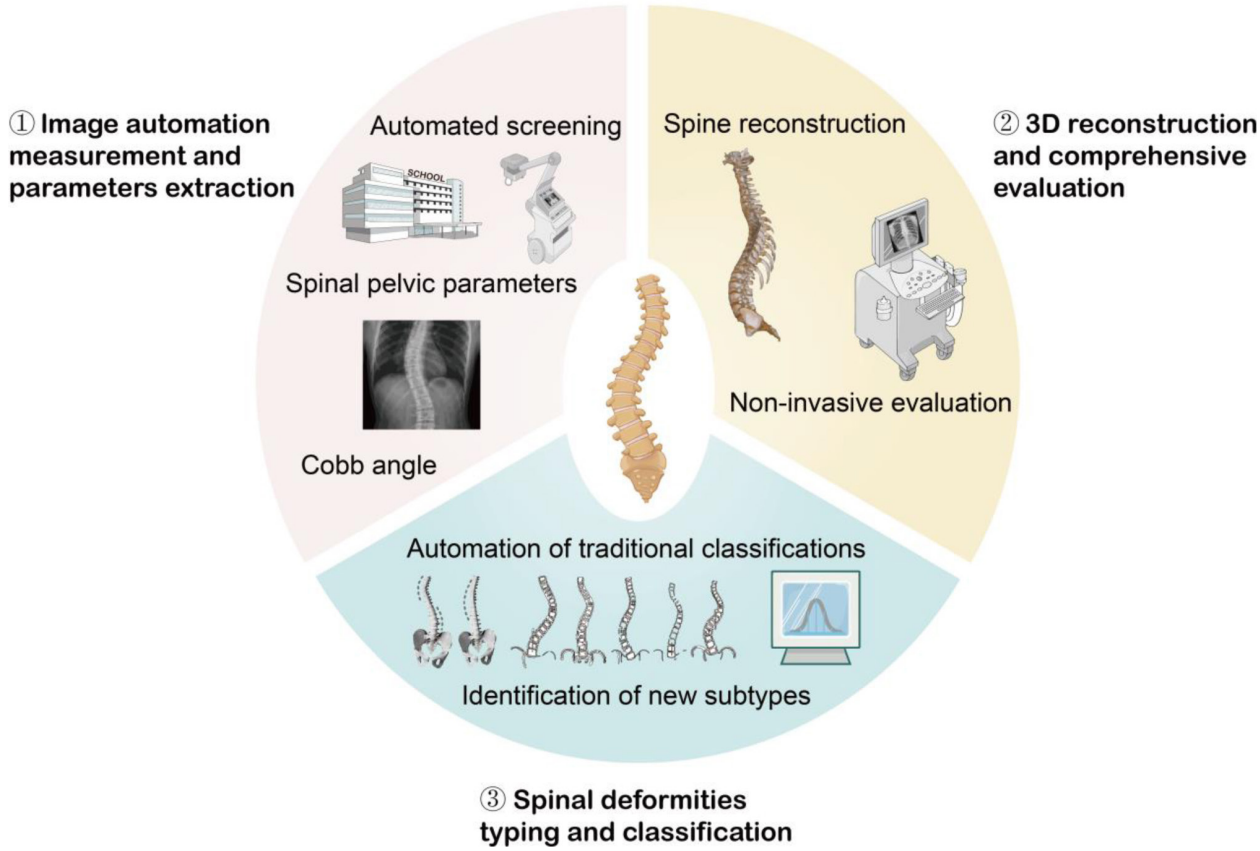


Figure 1. Application of AI in analysis and diagnosis of spinal deformities.

compensation, relative functional cross-sectional area of the paraspinal muscles, postoperative sacral slope, PT match, and sagittal age-adjusted score match.[53] Oh et al. successfully predicted the probability of achieving minimum clinically significant difference in oswestry disability index (ODI) after ASD surgery with 85.5% accuracy and 0.960 AUC.[54] Through latent profile analysis-based cluster analysis, Cui et al. revealed differentiated clinical characteristics and recovery trajectory among ASD patients, providing crucial reference for stratified management. The study utilized two years of follow-up data, enhancing long-term predictive value.[55]

Given the high complication rate and high cost of spinal deformity surgery, accurate operative assessment of individual patient risk is critical. Schonfeld et al. developed an LLM for predicting specific complications after ASD surgery, with preoperative clinical records as input. Test results demonstrated that the fine-tuned LLM outperformed CNNs in predicting pulmonary, neurological, and sepsis outcomes, with its sensitivity, specificity, and F1 score indicating potential for downstream clinical applications.[56] Scheer et al. developed a decision tree algorithm model incorporating baseline demographics, radiographic, and surgical factors to predict clinically significant proximal junctional kyphosis (PJK) and proximal junctional failure (PJF).[57] The model achieved an overall accuracy of 86.3% with an AUC of 0.890 and key predictors (importance ≥ 0.95) included age and preoperative SVA. Lee et al. also demonstrated that ML algorithms can accurately predict spinal-pelvic compensation after spinal fusion from the lower thoracic spine to the sacrum, through which the risk of PJK in the population can be reduced.[58] Ryu et al. used ML-based predictive algorithms and game theory to identify the main risk factors for unplanned reoperations after ASD correction surgery, namely postoperative SVA and PJF and their interactions, to achieve stratified management of high-risk patients.[59] Durand et al. used a CNN-based self-organizing map to perform cluster analysis on the sagittal morphology of ASD, and found that there were significant differences between different clusters in the relationship between kyphosis and PJK, so that surgeons could quickly compare the difference probability information.[60]

Lafage et al. found through cluster analysis that there were differences in the incidence of complications among groups of ASD surgical patients, but there was no significant difference in the types of complications, among which the main complication rate was highest in the severe sagittal cluster.[61] Based on a robust dataset of spinal X-rays (both screw-containing and screwless images), Lan et al. trained and tested a novel ethnicity–age–gender-adjusted Chinese ethnicity-tailored global alignment and proportion score (EAGA C-GAP) score, with superior accuracy in predicting mechanical complications (AUC = 0.627), setting a new benchmark for individualized prediction in Chinese population.[62] Yagi et al. constructed an ASD

postoperative complication prediction model with 92% accuracy and AUC of 0.963.[63] And the accuracy of external verification was 84%, which provided a scientific basis for physicians to evaluate the risk of complications in ASD patients in the 2-year postoperative period. Shahrestani et al. found that no algorithm can perform optimally on all perioperative indicators when evaluating the perioperative results of ASD surgery, such as logistic regression, random forest, gradient boosting machine and neural network, which indicated that the uniqueness of each outcome indicator must be fully considered to optimize individualized risk stratification of patients.[64]

AI reveals the natural course and surgical response of different types of patients according to their clinical and imaging characteristics, thus guiding more targeted treatment strategies.[65,66] Furthermore, the ability of AI models to identify and capture key image features or patient information without interference from other tissues or data needs further enhancement. The application of these AI models makes medical decisions no longer based solely on the correction of abnormalities, but more focused on the patient's subjective feelings and functional recovery, truly achieving a patient-centered treatment.

3.2. Surgical planning and intraoperative assistance

AI has now been integrated throughout the entire process of spinal deformity treatment decision-making and surgical planning, aiming to achieve safer and more effective personalized medical care. Spinal deformity correction surgery remains one of the most challenging procedures in spinal surgery, with an inherently unpredictable nature. Surgeons must carefully balance potential benefits such as correcting deformities, alleviating pain, and improving functional outcomes against significant risks including nerve damage, failure of internal fixation, and major complications.

The application of AI is moving from prediction to guidance, and it plays an important role in surgical planning. By integrating clinical, imaging, and biomechanical data, personalized surgical decision-making models can be built to assist surgeons in surgical classification, selection of optimal fusion segments and implant types. Constant et al. trained and validated an artificial neural network-based multitask learning model that demonstrates superior mixed-task prediction capabilities.[67] This model simulates the decision-making processes of experienced spinal surgeons during posterior spinal instrumentation and fusion, including selecting upper/lower instrumented vertebrae, determining rod curvature, and predicting screw density. The study of Lafage et al. simulated the decision process of senior surgeons in selecting the upper instrumented vertebra during thoracolumbar ASD correction surgery by ML algorithm, with accuracy rate of 81.0%, precision of 87.5%, and a recall rate of 87.5%.[68] More AI models targeting the screw dimension and path generation for patients with spinal deformities are expected to be developed to provide important reference for clinical practice.[69]

AI can also be integrated with robotic-assisted surgery to precisely execute preoperative plans during operations, thereby enhancing surgical accuracy and safety. AI assists in optimizing implantation designs for pedicle screws and iliac screws, recommending optimal corrective segments and strategies to achieve ideal postoperative alignment balance while minimizing surgical trauma.[70] Wang et al. reported the first AI-based spinal robotic system capable of preoperative independent planning of laminectomy paths and intraoperative automatic decompression execution. The accuracy, preliminary safety, and efficiency of this system were validated through cadaveric trials.[71] Robot-assisted techniques have their advantages in the upper thoracic segment and in cases of deformity, with easier and safer insertion of pedicle screws, a shorter learning curve for junior surgeons, and consistently good outcomes even at early stages of application. But the need for additional radiographic scans for the robotic assistance may result in higher radiation exposure, which still needs to be studied further.[72] In patients with severe complex spinal deformities, pedicle screw placement accuracy and major curvature correction rate of robot-assisted technology were comparable to those with non-severe deformities, and the incidence of complications was not significantly increased.[73] Singh et al. reported that the PJK rate observed in the AI-enhanced robotic group during 1-year follow-up was only 5.6%, compared with 32% to 35% in the traditional surgical group.[74] At 1-year postoperative follow-up, the loss of Cobb angle correction was less in the robot-assisted group (3.8° ± 1.8° vs. 4.9° ± 4.2°) compared with the traditional surgery group. Screw loosening occurred in 5.9% of cases in the robot-assisted group and 16.7% in the traditional surgery group, but no significant difference was observed.[75] Further research is still required on the perioperative and long-term outcomes as well as the correction effects of AI-enhanced robotic-assisted spinal surgery to support its clinical application and promotion.

The combination of augmented reality (AR), virtual reality (VR) system, and AI can superimpose 3D reconstructed images on the surgical field in real time, improve the accuracy of osteotomy and orthopedic correction, and promote the development of surgery to a more precise and minimally invasive direction. AR navigation technology has significantly improved the precision of spinal malformation internal fixation surgery, with high screw insertion accuracy of 98% and significant scoliosis correction effect.[76] Moreover, the rate of violation per patient was significantly reduced (7.5% vs. 6.6%, $p = 0.023$) for surgeons who received AR assistance, and the degree of fatigue was significantly improved (5.7 ± 1.7 vs. 3.3 ± 1.2, $p < 0.001$), which effectively improved the working happiness and stress resistance of surgeons.[77] Tu et al. developed a surgical system based on ultrasound image guidance and mixed reality technology, which can realize the insertion of pedicle screws by real-time soft

tissue deformation calculation, and significantly improve the efficiency and safety of pedicle screw insertion surgery.[78] However, it must be acknowledged that factors such as interocular distance, focal length, binocular parallax, and equipment dislocation may interfere with the operations of individual surgeons. Additionally, the high installation and maintenance costs pose significant barriers to the widespread adoption of navigation systems[79] (Fig. 2).

4. Current limitations and future directions

Although AI has shown great clinical application value in the diagnosis and treatment of spinal deformities, its clinical promotion still faces multiple challenges, and an urgent path for future development needs to be defined.

Current AI research in the field of spinal deformities is mostly retrospective, single-center studies with limited sample size and insufficient external validation.[80] There is a lack of large-scale, prospective, multicenter clinical studies with long-term (e.g., ≥ 5 years) patient outcomes data. This evidence gap limits the model's effectiveness and reliability across different populations and healthcare settings.[81] AI and ML models show promise for predicting PJK/PJF after ASD surgery, but larger multicenter studies with standardized definitions and preoperative MRI integration are needed for broader clinical application and validation.[82] Moreover, the data scope standards used by AI models require further improvement and standardization. Some studies excluded imaging data containing implants, simplifying the training and testing processes, which limits their application in real-world scenarios.[15,17,29] It may be necessary to develop tools specifically designed for implant analysis to enhance the generalizability of these models in the future.

In addition, access to medical data, privacy protection, and standardization of data protocols are also difficult.[83] The future focus is to establish open, standardized, high-quality multimodal databases that integrate multimodal information such as imaging, clinical, and genomics. On the other hand, attention should be paid to the balance between AI needs and patient rights protection, establishing a comprehensive system that integrates privacy-enhancing technologies such as federated learning, rigorous data governance policies, and transparent patient-centered ethical practices, to legally and compliantly unlock the potential of multicenter data.[84]

LLMs and multimodal large models have also demonstrated significant potential in the diagnosis and treatment of spinal deformities, with preliminary applications currently being employed in areas such

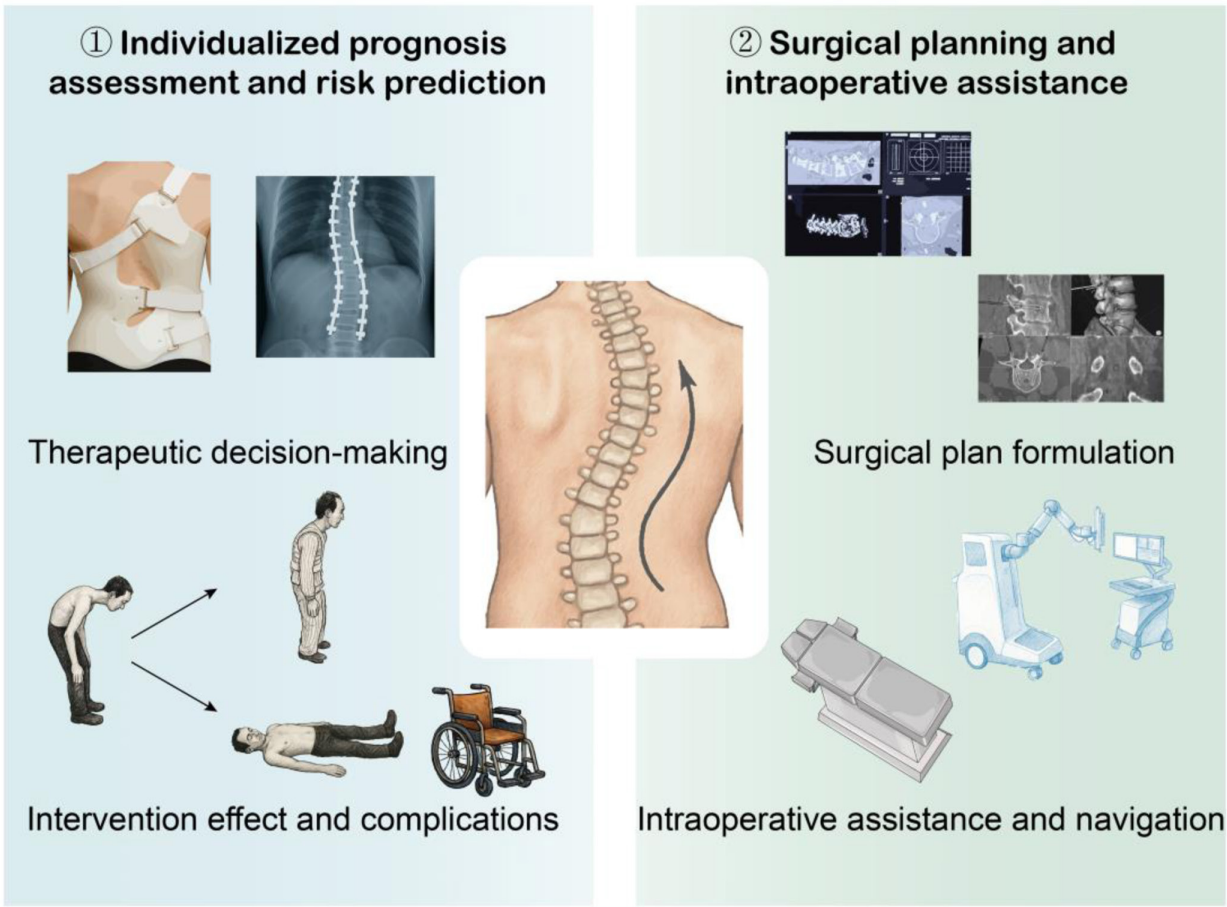


Figure 2. Application of AI in therapeutic decision and surgical planning of spinal deformities.

as auxiliary diagnosis, report processing, and patient education.[19,56,85] Zhao et al. constructed the spinal-specific multimodal dataset SpineMed-450k and the clinical evaluation framework SpineBench, and trained the SpineGPT model based on these datasets, which achieved an 87.44% score in spinal diagnostic tasks, significantly outperforming existing general and open-source models.[86] This study demonstrates that for specialized fields such as spinal diagnosis, which require complex anatomical reasoning, the development process of domain-specific instruction data and clinician intervention is key to achieving clinical-grade AI capabilities in the future. Another study demonstrated that a search engine incorporating GPT-4 provided relatively accurate and comprehensive responses when patients searched for spinal surgery information online.[87] Incorrect answers were corrected upon re-searching, with most information sourced from commercial websites. This research underscores the importance of continuous evaluation and improvement of LLMs to ensure reliable and informative results for patients during the integration of these models into search engines.

The complex processes of many AI models are like "black boxes" that are difficult for clinicians to understand and trust.[88] This not only hinders the application of AI in clinical decision-making, but also raises ethical and legal challenges regarding liability attribution. When AI recommendations lead to medical errors, the opaque decision-making process makes determining responsibility extremely difficult.[89] Developing AI models with enhanced transparency and interpretability is crucial, as this will help clinicians understand the decision-making rationale behind AI systems, build trust, and promote responsible implementation in clinical practice. For instance, visualizing the regions of interest of AI in imaging data; enhancing interactive elements to facilitate communication of decision-making processes; and quantifying the contribution of individual clinical features to decision-making—all aimed at "opening the black boxes" to ensure traceable application of AI. There is still a lack of research to interpret the technical architecture of explainable AI in the diagnosis and treatment of spinal deformities along with rigorous validation of clinical outcomes.[90]

Meanwhile, the rapid advancement of AI in healthcare is challenging existing regulatory frameworks. For the application of AI in spinal deformities, such as image analysis AI, surgical planning AI, or intraoperative navigation AI, rigorous clinical validation and approval are required, with accurate classification based on their risk levels.[91] On the other hand, postmarketing surveillance is equally critical. The current lack of sustained performance monitoring, safety event reporting, and real-world evidence-based re-evaluation makes it challenging to ensure the long-term safety and efficacy of AI in diverse clinical settings.[92] The supervision of AI in the diagnosis and treatment of spinal deformities is a dynamically evolving process, and addressing critical issues like ensuring product safety and efficacy, managing data ownership, obtaining informed consent from patients, and maintaining algorithmic fairness all require establishing robust legal frameworks and ethical guidelines.[93,94]

5. Conclusions

AI has been integrated into the entire process of spinal deformity diagnosis and treatment, demonstrating potential clinical applications from early evaluation screening to surgical decision-making and surgical assistance. It is gradually transforming diagnostic, therapeutic, and management approaches for spinal deformities. In terms of automated and standardized measurement of imaging parameters, AI effectively enhances diagnostic efficiency and consistency. By combining cluster analysis, image segmentation, and multimodal data integration, AI significantly improves the objectivity and scientific rigor of spinal deformity classification (Fig. 1). Additionally, AI's application potential in surgical planning and risk prediction continues to grow, driving personalized treatment for spinal deformities. Surgical assistance systems integrating robot navigation with AI have improved surgical outcomes and accelerated physicians' professional development (Fig. 2).

However, data universality, algorithmic explainability, and ethical considerations remain critical bottlenecks in AI clinical applications. Future efforts should focus on conducting high-quality, multicenter, long-term clinical validation studies to provide robust evidence for AI's effectiveness and safety. Accelerating the development and application of explainable AI technologies will help demystify decision-making processes and build clinical trust. Simultaneously, advancing regulatory frameworks and standardizing oversight mechanisms are essential to enhance tangible benefits for patients with spinal deformities.

The transition from clinical validation to widespread application of AI in spinal deformity treatment marks a shift from the era of "empirical medicine" to a new age integrating "precision evidence-based medicine" and "data-driven medicine". We are confident that AI will soon become an indispensable force in the prevention and treatment of spinal deformities.

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Conflicts of interest

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Author contributions

HW, YC, CJ—conceptualization.
CJ, HS, ZC—methodology.
CJ, HS, YH—investigation.
CJ, HS—writing-original draft.
HW, YC—writing-review and editing.
CJ, JL—visualization.
XM, FL, JJ—supervision.
HW, YC—project administration.
HW—funding acquisition.

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