Review

SPINE RESEARCH

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Artificial intelligence in spine research

A multimodal perspective beyond imaging

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Abstract

Recent advances in artificial intelligence (AI) have brought significant progress to the field of spine research. While image-based AI applications such as automated spine segmentation and pathology detection have garnered substantial attention, the potential of AI beyond imaging data remains less explored. These applications include predictive models built on electronic health records and spine registries, analytics of wearable sensors, genomics and other "omics" data, and AI-driven robotics for surgery. This review provides a comprehensive overview of AI applications in spine research from a multimodal perspective, tracing their historical development, highlighting current progress, and addressing key challenges including data integration, explainability, and regulatory hurdles. Additionally, we outline future directions to highlight AI's expanding role in precision medicine, clinical decision-making, and ultimately the enhancement of patient outcomes in spinal disorders.

Keywords: AI-driven robotics, artificial intelligence, data integration, electronic health records, genomics/omics data, medical imaging, precision medicine, spine research, wearable sensors

1. Introduction

Spinal disorders impose a major socioeconomic and health burden worldwide, leading to substantial healthcare costs and reduced quality of life for millions of people.[1] Traditionally, the evaluation of spinal pathologies has predominantly relied on imaging modalities such as radiography, computed tomography (CT), and magnetic resonance imaging (MRI). In recent years, artificial intelligence (AI) has shown considerable potential in improving the efficiency and accuracy of spine-related diagnoses, treatments, and prognoses.[2] However, AI applications are not limited to imaging. With the continuous expansion of medical data, diverse data modalities such as electronic health records (EHRs), wearable sensors, and genomics are increasingly integrated into spine research (Fig. 1).[3–5]

To ensure a comprehensive and up-to-date synthesis of these developments, we conducted a systematic literature search in PubMed, Embase, Web of Science Core Collection, IEEE Xplore, and Scopus for articles published between January 1, 2016 and December 31, 2024. The Boolean query, ("spine" OR "spinal" OR "vertebra*") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*") AND ("multimodal" OR "omics" OR "EHR" OR "wearable*" OR "robotic*"), was adapted to the controlled vocabulary and field tags of each database. Duplicate records were removed, and titles, abstracts, and full texts were screened by 2 independent reviewers; discrepancies were resolved by consensus. The complete search strings are provided in Table S1, Supplemental Digital Content, https://links.lww.com/SPRES/A1.

This review aims to:

1. provide a historical overview of how AI has been applied in spine research;
2. summarize the current landscape of AI applications that extend beyond imaging, including EHR-driven predictive models, wearable sensor data analysis, and omics-based approaches;
3. discuss the complementary roles of nonimaging and imaging data in achieving a comprehensive understanding of medical conditions caused by spinal disorders;
4. outline the major challenges and barriers to clinical implementation of multimodal AI solutions in routine spinal care;
5. present future perspectives for AI-driven innovations in advancing personalized and precision medicine for spinal disorders.

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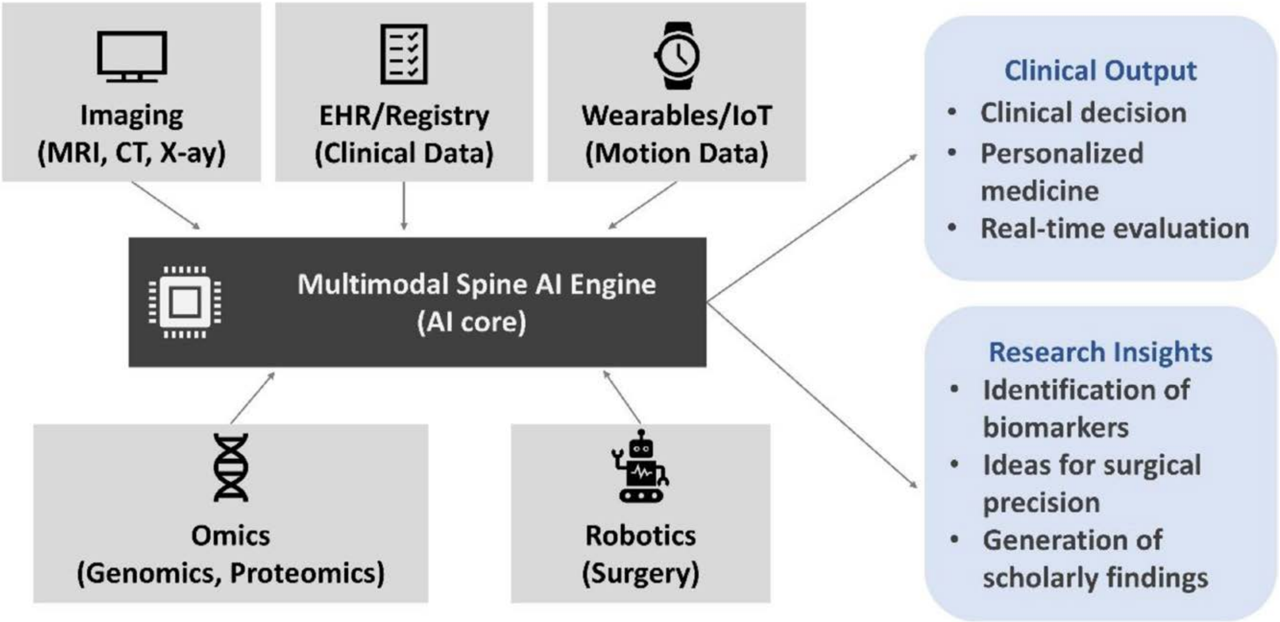

Figure 1. The conceptual diagram of a multimodal AI platform for spine-related diagnoses, treatments, and prognoses. Multiple data sources—including imaging (MRI, CT), EHR (electronic health records)/registries (clinical data), wearables/IoT devices (movement, posture), omics (genetic/proteomic information), and surgical robotics—feed into an AI core. This AI engine analyzes and integrates the inputs to generate clinical outputs (e.g., decision support, risk assessment, and personalized treatment plans) and research insights (e.g., biomarker discovery and novel algorithm development), aiming to improve overall patient outcomes in spinal disorders. AI = artificial intelligence; CT = computed tomography; IoT = internet of things; MRI = magnetic resonance imaging.

2. Historical overview of AI in spine research

2.1. Early AI adoption: rule-based and conventional machine learning

Early applications of AI in spine care were largely rule-based expert systems and conventional machine learning (ML) models, such as decision trees, support vector machines, and Bayesian approaches.[6–8] These methods primarily focused on:

- basic classification tasks (e.g., spinal fracture *vs* nonfracture, scoliosis *vs*. nonscoliosis) and
- predicting surgical outcomes based on structured clinical data from spine registries.

While AI-driven image analysis did gain some early traction, its progress was constrained by limited computational resources, small data sets, and nonuniform imaging protocols, restricting these efforts to proof-of-concept studies.

2.2. Emergence of deep learning and big data

By the mid-2010s, deep learning revolutionized medical image analysis, accelerating the interest in AI for spinal imaging.[9] Concurrently, large-scale databases and national spine registries (e.g., the North American Spine Society registry) emerged, providing extensive data resources for ML-driven predictive modeling. As EHR systems became widespread, the diversity and volume of clinical data significantly increased, enabling more sophisticated multifactorial risk models for spinal disorders. This paradigm shift laid the foundation for AI approaches that integrate imaging with nonimaging data sources.[10]

3. AI applications beyond imaging

Although AI-based imaging analysis often dominates discussions, nonimaging modalities—such as EHR data, wearable sensor outputs, and omics—hold tremendous potential for advancing spine care (Table 1). This section highlights key applications and recent progress in these emerging areas.

3.1. EHRs and registries

3.1.1. Clinical decision support. Integrating EHR data into AI algorithms allows real-time clinical decision support in spinal care. For instance, AI models have been developed to:

- predict perioperative risks such as 30-day readmission and surgical site infections by analyzing comorbidities, medication history, and laboratory values[3] and
- use natural language processing to extract key details from physician notes and operative reports (e.g., surgical approach, specific implants used, and documented intraoperative complications), thereby enhancing outcome prediction accuracy.[11–13]

3.1.2. Outcome prediction. Large registries tracking thousands of spine surgeries provide valuable longitudinal data for AI-driven outcome prediction. These include:

- fusion success and hardware failure rates after lumbar or cervical fusion surgeries and
- probability of revision surgery in adult spinal deformities based on multicenter data.

ML models have demonstrated the ability to identify complex patterns in multidimensional patient profiles,

Table 1

Overview of nonimaging data modalities in spine research.

Modality	Main applications	Advantages	Limitations
EHR/registries	CDS (clinical decision support) Outcome prediction	Large-scale, real-world data Longitudinal tracking	Data heterogeneity Limited structure
Wearables/IoT	Motion/posture monitoring Remote rehabilitation and coaching	Continuous data Early detection of deterioration	Device calibration User compliance
Omics	Genomic risk stratification Multiomics integration	Mechanistic insights Personalized treatment	Complexity Ethical/privacy issues
Robotics	Surgical planning Intraoperative guidance	Enhanced precision Reduced surgical errors	High cost Requires specialized training

EHR = electronic health records; IoT = internet of things.

surpassing conventional regression-based methods in predicting complications and reoperation risk.[14]

3.2. Wearable sensors and internet of things devices

3.2.1. Motion analysis and posture monitoring. Wearable sensors (e.g., accelerometers, gyroscopes, and smartwatches) enable continuous monitoring of spinal patients in real-life settings.[4] AI algorithms can analyze these data streams to detect:

- changes in gait and mobility, which may indicate disease progression, postoperative complications, or poor postoperative recovery;
- subtle posture deviations associated with pain exacerbations in chronic back pain patients.

These insights facilitate real-time feedback for both patients and clinicians, supporting timely interventions and fostering more proactive management of spinal disorders.[15]

3.2.2. Remote rehabilitation and coaching. AI-powered wearable systems facilitate tele-rehabilitation by guiding patients through prescribed exercises, monitoring adherence, and detecting incorrect or compensatory movements.[16] ML-driven automated feedback systems provide personalized prompts, enhancing patient engagement and potentially improving rehabilitation outcomes.

3.3. Genomics and other "omics" data

3.3.1. Genetic foundations of spinal diseases. Certain spine conditions (e.g., adolescent idiopathic scoliosis and intervertebral disc degeneration) have known hereditary components.[17] AI-based analyses of large-scale genomic datasets (e.g., genome-wide association studies) can identify novel risk loci and gene–environment interactions, advancing the understanding of genetic predisposition to spinal diseases.[18]

3.3.2. Multiomics integration. Transcriptomics, proteomics, and metabolomics offer additional layers of information on spinal pathology, such as inflammatory or degenerative processes. Multiomics AI platforms combine these datasets with imaging and EHR data to:

- classify disease subtypes (e.g., degenerative disc disease) based on molecular signatures[19,20] and
- predict patient-specific responses to therapeutic interventions (e.g., biologics or cell-based therapies).[5]

3.4. Robotics and navigation

3.4.1. Surgical planning and intraoperative guidance. While robotic-assisted spine surgery has traditionally depended on preoperative imaging guidance, next-generation AI systems incorporate intraoperative sensor data (e.g., force/torque feedback and real-time tracking) to optimize screw trajectory and reduce complications.[21] AI-enhanced algorithms can:

- adapt drill paths real-time adjustments based on changes in bone strength or tool deviation;
- alert surgeons to high-risk maneuvers, enhancing procedural safety and efficiency.

3.4.2. Augmented and virtual reality. Extended reality technologies combined with AI are emerging as navigation aids that superimpose spinal anatomical landmarks and real-time surgical data in the surgeon's field of view.[22] This integration surpasses traditional static imaging by allowing dynamic, data-driven overlays of critical structures, thereby minimizing guesswork and streamlining surgical workflows.

4. Integration with imaging data

In the past 3 years, deep learning–based computer vision techniques have driven significant advances in spinal imaging analysis. State-of-the-art models now achieve automated vertebral and disc segmentation, as well as high-accuracy classification of spinal pathologies (e.g., disc herniations and vertebral fractures), often matching expert-level performance.[23] Concurrently, generative adversarial networks and other generative models are being utilized to augment imaging datasets and enhance MRI/CT quality—for instance, by synthesizing high-fidelity images or even generating CT scans from MRI data—thereby addressing data scarcity and improving diagnostic model robustness.[24] Despite the focus on nonimaging modalities above, imaging remains a cornerstone of spinal diagnostics. Consequently, the most advanced AI applications often merge imaging data with complementary data sources to provide a multidimensional patient assessment. Examples include the following:

- predictive modeling of postoperative outcomes, incorporating MRI-derived parameters (e.g., disc degeneration grade) with EHR-based risk profiles.
- wearable sensor data (e.g., changes in gait speed, step count, or posture) can be cross-referenced with radiographic indicators of spinal instability (e.g., flexion–extension X-ray findings or vertebral slippage) to provide a more dynamic assessment of degenerative spinal diseases. By correlating functional mobility limitations with structural changes, clinicians gain deeper insight into how imaging-detected abnormalities translate into real-world physical impairments, allowing for more tailored interventions and closer monitoring of disease progression.

Such integrated approaches are demonstrating improved prognostic accuracy compared to single-modality analyses.[10,25,26]

5. Challenges

5.1. Data quality and standards

Ensuring standardization in nonimaging data is at least as challenging as managing imaging protocols. Disparate EHR systems, variations in wearable device calibration, and complex omics workflows hamper data interoperability.[27] Moreover, robust, deidentified datasets are needed to mitigate privacy risks, especially when dealing with genetic and continuous wearable data.

5.2. Explainability and trust

As AI models become more complex, clinicians face the challenge of interpreting these "black box" systems, especially with multimodal data. Although first-generation explainability techniques like SHapley Additive Explanations, which attributes feature contributions and attention-based neural architectures have improved interpretability, newer XAI methods—such as Gradient-weighted Class Activation Mapping and counterfactual explanations—have been proposed to further illuminate model decision-making.[28] However, a broad consensus on the optimal approach to ensure clinical reliability and foster trust in AI predictions has yet to be established.

5.3. Generalizability

Overfitting to specific datasets is a constant challenge in AI models. Models trained on a single institution's EHR and wearable data may not generalize across diverse populations with varying genetic backgrounds, social determinants of health, or technology usage patterns.[29] To ensure robust clinical applicability, continuous validation and external, multicenter collaborations are essential.

5.4. Workflow integration

Effective use of AI tools in daily practice requires:

- seamless software integration with existing hospital information systems;
- minimal disruption to clinical routines, which means intuitive interfaces and a clear added value for care teams;
- adequate training for clinicians to interpret AI predictions and incorporate them into decision-making processes.

5.5. AI adoption in spine surgery: key challenges and considerations

The integration of AI into spine surgery represents a significant paradigm shift, but its widespread adoption faces substantial challenges, particularly in economic feasibility and business strategy. Various commercialization models, including corporate acquisitions and subscription-based services, are being explored to mitigate the financial burden associated with AI-assisted surgical planning systems. The high cost of these systems remains a concern, limiting them mostly to well-funded centers and raising questions about who ultimately pays. Different healthcare systems must address this challenge through context-specific strategies. For instance, while hospitals in the United States may justify the financial investment in AI-driven surgical planning systems based on anticipated improvements in patient outcomes and institutional reputation, hospitals in Japan may delay adoption until more favorable reimbursement policies are established. Moving forward, continued innovation is likely to drive costs down and integration up: more competition, smarter AI, and supportive policies could make these advanced spine surgery tools commonplace rather than rarities. The coming years will reveal how quickly these promising technologies can surmount financial hurdles and deliver value at scale—ensuring that patients globally can benefit from safer, more precise spine surgeries without undue cost burden.[30,31]

5.6. Ethical and regulatory considerations

From data sharing and privacy (The Health Insurance Portability and Accountability Act of 1996 , The General Data Protection Regulation) to liability in AI-driven surgical decisions, the ethical and legal landscape is complex.[32] Genomic data pose particularly sensitive ethical concerns regarding consent and potential discrimination. Regulatory frameworks, including those from the US Food and Drug Administration and European Medicines Agency, are evolving to address the approval pathways for AI-based medical devices.[33,34]

6. Future directions

6.1. Multimodal data integration

High-throughput omics, real-world data from wearables, and large-scale imaging repositories can be fused into comprehensive longitudinal patient models. Techniques like federated learning, which allows an AI model to learn from data spread across multiple locations (like different hospitals or smartphones) without copying or collecting all the data in one place, will help train robust AI algorithms without necessitating centralized data storage, thus preserving patient privacy.[35]

6.2. Personalized medicine

AI has the potential to drive the advancement of precision spinal care by integrating genetic, molecular, and real-time physiological data to guide individualized treatment plans. Personalized risk assessment tools, advanced rehabilitative strategies, and biologic interventions tailored to molecular subtypes all stand to benefit from AI-based analytics.[36]

6.3. Next-generation robotics and augmented and virtual reality

AI-driven surgical robotics combined with augmented and virtual reality could transform spine surgery, reducing complications and enhancing surgical education. Future systems may incorporate machine vision, force feedback, and predictive analytics to provide truly adaptive robotic assistance.[37]

6.4. Generative AI and NLP

Generative models (e.g., generative adversarial networks and large language models) may:

- create realistic synthetic spine datasets to improve model training[24];
- summarize operative reports and patient records for quick reference;
- offer advanced decision support by combining imaging findings with textual EHR data in real time.[38]

6.5. Regulatory harmonization

As AI technology continues to advance, international collaborations and guidelines will shape best practices for algorithm development, validation, and postmarket surveillance. Clear metrics for safety and efficacy will facilitate clinical translation and trust among stakeholders.

7. Conclusion

The application of AI in spine research now extends far beyond imaging. Integrated analyses of EHR data, wearable sensors, genomics, and robotics are converging to offer a more holistic perspective on spinal pathologies and patient care. Despite the rapid progress in AI-driven innovations, significant challenges remain such as data standardization, model explainability, and regulatory frameworks. Continued collaborative efforts among clinicians, data scientists, engineers, and policymakers are essential for realizing the transformative potential of multimodal AI in spine care. By pushing the boundaries beyond imaging alone, the field is well-positioned to personalized, efficient, and data-driven solutions that can significantly improve outcomes for patients with spinal disorders.

8. Use of generative AI

During the preparation of this manuscript, ChatGPT-4o (OpenAI) was used solely for English language refinement and translation support. All content was critically reviewed and edited by the authors to ensure accuracy and originality.

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KK drafted the manuscript. TK supervised and critically revised the manuscript.

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