Review

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Review

Intelligence Architectures and Machine Learning Applications in Contemporary Spine Care

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Abstract: The rapid evolution of artificial intelligence (AI) and machine learning (ML) technologies has initiated a paradigm shift in contemporary spine care. This narrative review synthesizes advances across imaging-based diagnostics, surgical planning, genomic risk stratification, and post-operative outcome prediction. We critically assess high-performing AI tools, such as convolutional neural networks for vertebral fracture detection, robotic guidance platforms like Mazor X and ExcelsiusGPS, and deep learning-based morphometric analysis systems. In parallel, we examine the emergence of ambient clinical intelligence and precision pharmacogenomics as enablers of personalized spine care. Notably, genome-wide association studies (GWAS) and polygenic risk scores are enabling a shift from reactive to predictive management models in spine surgery. We also highlight multi-omics platforms and federated learning frameworks that support integrative, privacy-preserving analytics at scale. Despite these advances, challenges remain—including algorithmic opacity, regulatory fragmentation, data heterogeneity, and limited generalizability across populations and clinical settings. Through a multidimensional lens, this review outlines not only current capabilities but also future directions to ensure safe, equitable, and high-fidelity AI deployment in spine care delivery.

Keywords: spine surgery; artificial intelligence; machine learning; predictive modeling; neural networks; spinal diagnostics; computer vision; surgical robotics; clinical decision support; biomedical informatics; musculoskeletal imaging; outcome prediction; precision medicine

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Introduction

In this comprehensive narrative review, we analyze how artificial intelligence (AI) and machine learning (ML) technologies are shaping contemporary spine surgery and spine care. By examining advanced applications from diagnostic imaging to predictive genomics, we take an in-depth look at how sophisticated AI algorithms are revolutionizing multiple domains of orthopedic and spine-focused medicine, including automated radiological interpretation, surgical planning optimization, robotic-assisted procedures, and personalized risk stratification through genomic analysis. Current evidence demonstrates that AI-powered systems such as Aidoc's cervical spine fracture detection [1], Zebra Medical Vision's vertebral compression fracture identification [2], and SpineNet's comprehensive spinal pathology analysis [3], among other systems and software, achieve diagnostic accuracies comparable to or exceeding specialist radiologists. In essence, we strongly believe that at the very least, these tools can be used alongside clinician practice as a secondary guide. Furthermore, emerging clinical decision support platforms, including Suki AI, Nuance Dragon Ambient eXperience (DAX), and Ambience Healthcare, are streamlining documentation workflows and

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enhancing physician-patient interactions through ambient intelligence capabilities [4]. In a similar vein, as many robotic systems like the Mazor X Stealth Edition, ExcelsiusGPS, and ROSA Spine with AI-driven surgical planning are being increasingly tested and even taught to incoming residents [5], we believe there is an ongoing shift toward precision-guided interventions that minimize invasive approaches while maximizing surgical accuracy. Genomics is also finding its role into risk prediction and stratification, as genome-wide association studies (GWAS) and deep learning models are enabling new insights into genetic predispositions for pathologies and outcomes alike, thus allowing clinicians to now factor in patient-specific risk profiles [6]. In this review, we synthesize current evidence across these diverse applications while addressing implementation challenges, regulatory considerations, and future directions for AI integration in spine care.

Current Applications of AI in Imaging and Radiological Analysis

I. Automated Detection and Classification of Spinal Pathologies

AI, and more importantly, the resultant sophisticated deep learning algorithms capable of detecting and classifying complex pathological conditions, have largely changed clinical practice. For instance, convolutional neural networks (CNNs) have been proven to automatically identify vertebral compression fractures [7]. As a use case, Zebra Medical Vision's FDA-approved HealthJOINT system demonstrates significant clinical utility in reducing under-detection rates of these frequently missed injuries [8]. With tools such as the HealthJOINT system, clinicians may be able to diagnose faster and have more trust in their diagnosis. Ideally, when clinician opinion is confirmed by HealthJOINT system imaging, all parties can have greater confidence in treatment decisions. This also helps patients as it introduces a new “check-and-balance” at the bedside.

Fortunately, the diagnostic accuracy of these AI systems are being increasingly strictly evaluated. The urgency of addressing this issue is heightened as numerous AI systems have previously been found to enter clinical settings without undergoing thorough validation by the U.S. Food and Drug Administration (FDA) prior to 2025. For example, a study by Clark et al. revealed that among 119 medical devices marketed as AI- or ML-enabled, 23 (19.3%) had discrepancies or ambiguities between their advertised capabilities and actual FDA clearance [9]. Moreover, many AI/ML tools undergo validation using synthetic or “phantom” datasets, which often fail to capture the complexity of real-world clinical conditions. Supporting this concern, Chouffani El Fassi et al. found that 226 out of 521 FDA-approved AI-enabled clinical devices lacked peer-reviewed clinical validation and had not been trained on actual patient data [10]. These findings underscore the pressing need for regulatory bodies to enhance FDA oversight, enforce stricter validation standards, and implement mechanisms for ongoing, real-time performance monitoring. In the absence of clinically representative training data and post-market surveillance, opaque or “shadow” AI systems risk perpetuating bias, compromising patient safety, and obscuring liability.

A clear recent example of increased FDA regulation is Aidoc's cervical spine algorithm receiving FDA clearance and demonstrating consistent performance across diverse patient populations [11]. Real-world implementation data from multiple healthcare institutions reveal that AI-assisted triage systems can reduce radiologist interpretation time while maintaining high sensitivity for acute fractures. However, recent external validation studies have highlighted important limitations, particularly in detecting chronic fractures and subtle pathological changes amid varying fracture characteristics and imaging quality [12,13]. This is a cautionary tale to developers and hospital administration alike. Essentially, all parties must ensure continuous model refinement and, if needed, failure mode analysis to optimize clinical performance.

A main concern that orthopedic specialists had was a lack of automated segmentation. New tools such as SpineNet by Jamaludin et al. [14], represents fills this gap and is a landmark achievement in comprehensive spinal analysis. Specifically, SpineNet can automate segmentation and label spine structures across various imaging modalities, like CT and MRI [15]. This is very useful for layering multiple imaging types and doing a comprehensive grading of disc degeneration, assessing central canal stenosis, and spondylolisthesis quantification. SpineNet has also shown capability to simultaneously evaluate Pfirrmann grades, endplate defects, marrow changes, and foraminal stenosis within a single analytical framework. Fortunately, many similar platforms are emerging and external validation studies have confirmed that these platforms are beginning to show consistent performance across different institutional, socioeconomic, and patient settings (e.g. rural, urban, etc) [16,17].

II. Advanced Morphometric Analysis and Quantitative Assessment

Clinicians conducting morphometric analysis can especially benefit from emerging AI technologies that are now used at the bedside. For example, traditional manual Cobb angle measurements have 95% confidence intervals (CIs) ranging from 4° to 8°, while AI-assisted measurements demonstrate significantly improved consistency with mean absolute errors consistently below 3° [18].

Deep learning models such as the two-stage ensemble models described by Yeh et al. (2021) demonstrate exceptional automated landmark detection and angular measurement performance, localizing 45 anatomic landmarks and generating 18 radiographic parameters on whole-spine lateral radiographs [19]. They also proved effective when analyzing even in off-center, angulated, and technically suboptimal images. These models, trained on large annotated datasets, have shown mean errors and correlation values comparable to expert clinicians for many parameters [20–22]. This effectiveness also extends to automated Cobb angle measurement. For example, the cobbAngle Pro app uses a proprietary deep learning pipeline to eliminate manual landmark selection and surprisingly, achieves repeatable measurements across mild, moderate, and severe scoliosis cases [23,24]. This seems very helpful for clinicians working in the field (e.g. in combat settings, rural and resource limited areas, or in underfunded urban hospitals), as they can upload spinal X-rays from their mobile devices and still take advantage of the AI/ML-powered tool. Fortunately, the app's underlying model has shown to be in agreement with expert readers and is available as a commercial product for clinical use [24].

Another promising area of advancement is in ultrasound-based spine imaging. The ultrasound global guidance block network (UGBNet) offers fully automatic segmentation of bony features [25]. Notably, it has been shown to work with low-contrast, noisy ultrasound images. In fact, spatial and channel attention-mechanism integrated UNets have been shown to outperform traditional UNet architectures in segmentation precision [26] and is even referenced in peer-reviewed literature for its clinical feasibility [27–29]. Automated measurement systems are also being increasingly used to quantify multiple parameters such as coronal vertical axis, sagittal vertical axis, thoracic kyphosis, lumbar lordosis, T9 spinopelvic inclination, frontal pelvic asymmetry, sacral slope, pelvic tilt, and pelvic incidence [30,31].

Another advanced development is tissue segmentation. Models are now demonstrating automated quantification of paravertebral muscle characteristics, including cross-sectional areas and fatty infiltration patterns that correlate with functional outcomes and disability measures. A primary example of this is the CTSpine1K dataset, which has annotations for over 11,000 vertebrae including both healthy and pathological specimens [32]. The main benefit of CTSpine1k and related datasets, especially open source datasets such as those available on TrinetX [33], is that they can objectively measure muscle quality and quantity on a large scale, thus enabling smaller research groups to study pathology and incidence without necessarily needed an IRB-dictated patient cohort.

Surgical Planning and Robotic-Assisted Interventions

I. Advanced Preoperative Planning and Simulation

One main benefit that AI/ML systems can have on spine surgery is preoperative planning. For example, modern AI-powered planning platforms utilize sophisticated algorithms to analyze patient-specific anatomy from CT and MRI datasets, thus generating comprehensive three-dimensional models that facilitate optimal surgical approach selection and hardware placement planning [34]. The Mazor X Stealth Edition robotic guidance system is a key example of this integration as it enhances

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precision by integrating advanced surgical predictive software with active human-guided robotic support and navigation for minimally invasive procedures [35]. In terms of training, many of these robotic systems prove useful as surgeons and trainees alike can perform virtual simulations, test different approaches and implant configurations beforehand, and ultimately use the systems as an aid for risk assessment and stratification.

Another important system is the ExcelsiusGPS system, which can generate real-time information before and during procedures [35,36]. For example, a spine surgeon can use the system's robotic navigation to precisely place screws and rods across cervical to sacroiliac spinal regions. Advanced algorithms will then analyze bone density patterns, cortical thickness measurements, and trabecular architecture to optimize screw trajectory planning and predict pullout strength characteristics. This level of detailed preoperative analysis is particularly valuable in challenging cases involving osteoporotic bone, complex deformities, or revision procedures where anatomical landmarks may be altered or obscured by previous surgical interventions [37]. Such alterations might not even be accounted for by surgeons, and thus a combined approach using both the Mazor X robot and the ExcelsiusGPS system can help clinicians rule out any risk factors. The AI-Driven FEA Simulator integrates finite element analysis with multimodal imaging to minimize implant complications through personalized biomechanical optimization [38].

II. Robotic-Assisted Surgical Execution

Existing surgical platforms like ROSA Spine and da Vinci SP are being integrated or even overtaken by next-generation systems that use AI-driven navigation and adaptive control to redefine intraoperative accuracy [39]. DePuy Synthes' VELYS™ Active Robotic-Assisted System, created in conjunction with eCential Robotics, offers dual-use capabilities, integrating independent navigation and active robotics to customize surgical guiding for surgeon preferences and pathological processes [40]. This system is FDA-cleared for spinal fusion surgeries in the cervical, thoracolumbar, and sacroiliac areas, and it complements DePuy Synthes' core spine portfolio, which includes the SYMPHONY OCT, TriALTIS, VIPER PRIME, and EXPEDIUM VERSE systems [40,41]. The VELYS Adaptive Tracking Technology and VELYS Trajectory Assistance allow for real-time correction of robotic trajectories in response to intraoperative imaging and patient movement, providing excellent implant placement even in anatomically complex or revision situations.

Additionally, multimodal imaging analysis is being combined with robotic capabilities. A prime example of this is Medtronic's VELYS platform and Mazor Robotic Guidance System now using AI-powered analytics to dynamically alter surgical plans and robotic trajectories based on intraoperative CT, fluoroscopy, and MRI data [42]. This allows for continuous verification of surgical progress and fast correction of errors, with AI algorithms recognizing variations between intended and actual implant placements and automatically recalibrating robotic guiding. The end result is a closed-loop feedback system in which preoperative simulations, intraoperative imaging, and robotic execution are closely linked. On top of hardware, software platforms are also advancing. For example, the eCential Robotics Spine Suite offers a single software environment for preoperative planning, intraoperative navigation, and robotic execution, enabling surgeons to easily switch between imaging modalities and surgical stages [43–45]. This integration allows pathology-specific planning, in which AI algorithms assess patient anatomy, bone quality, and biomechanical risk factors to offer the best implant designs and surgical techniques. The program also offers real-time data visualization, enabling surgeons to interact with 3D spine models and change robotic trajectories during the procedure. This intraoperative adaptive control be can be even further improved by AI-driven predictive analytics. The VELYS and Mazor platform systems for example use ML models that are trained on past procedures. If intraoperative imaging uncovers unanticipated anatomical variation or other known risk factors, the system may automatically recalculate ideal screw trajectories and update robotic guidance, decreasing the need for human intervention and the likelihood of postsurgical problems. However, if data can be shared across cloud-based analytics platforms, such as those being developed by DePuy Synthes and other industry leaders, future developers can integrate real time data into their ML algorithms as opposed to only previously published datasets

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[46]. In this sense, new surgical techniques and assessments can be integrated into the VELYS or Mazor platforms to keep the robotic systems up-to-date. Patient privacy can also be protected here by using federated learning techniques and training AI models on distributed datasets.

III. Integration with Advanced Navigation and Guidance Systems

Modern navigation and guidance in spine surgery is increasingly using real-time adaptive control, exemplified by platforms such as the Brainlab Curve Navigation System [47], which integrates AI-driven 3D navigation with intraoperative CT and fluoroscopy for automatic registration and continuous real-time tracking, substantially improving pedicle screw placement accuracy while reducing setup time. The Stryker NAV3i Navigation System [48] can automatically anatomical-landmark and adapt navigation, streamlining workflow and enhancing precision in complex deformity cases. Medtronic StealthStation S8 further advances the field with AI modules that enable continuous error correction, multimodal imaging integration, and predictive navigation, supporting FDA-cleared workflows that adapt dynamically to intraoperative changes and patient-specific anatomy [49]. In a similar manner, Zimmer Biomet ROSA ONE Spine and NuVasive Pulse Platform demonstrate the integration of AI-powered trajectory planning, augmented reality visualization, and real-time feedback, enabling surgeons to anticipate procedural needs and optimize navigation parameters throughout each surgical step [50–52]. These systems collectively represent the next generation of navigation technology, where predictive analytics, cloud-based learning, and federated data sharing ensure continuous improvement in surgical accuracy and safety across diverse clinical environments.

IV. Functional Outcome Prediction and Treatment Optimization

Frameworks like Graph Neural Networks (GNNs), Generative Adversarial Networks (GANs), and Transformer-based architectures are being integrated into spine care in order to help clinicians analyze complex, non-linear relationships between preoperative imaging, patient-reported outcomes, and longitudinal psychosocial data to uncover subtle predictors of recovery and satisfaction [53–56]. In terms of psychological recovery, emerging NLP platforms are using sentiment analysis to extract psychological and emotional cues from patient interviews, electronic health records, and digital diaries [57–59]. This is especially beneficial for cross-disciplinary care, where trauma surgeons may work with psychiatrists and other mental health professionals to assess post-surgical anxiety, depression, or poor adaptation-factors now recognized as critical determinants of long-term functional success. Wearable sensors are also finding a role in this domain as devices like ActiGraph GT9X and WHOOP Strap 4.0 are being used to track sleep quality, activity patterns, and physiological stress responses following surgery [60,61]. This can subsequently feed into measures like the Oswestry Disability Index and visual analog scale scores to obtain a comprehensive picture of patient recovery. This increased ease of obtaining comprehensive health information is further supported by Federated Learning and Edge AI architectures [62], which can protect patient privacy while also securely transmitting data between research groups and academic centers.

V. Cost-Effectiveness Analysis

Recent developments in healthcare economics have introduced a range of advanced models and theories to optimize cost-effectiveness and resource allocation in spine care, including value-based healthcare frameworks, bundled payment models, and population health management systems that prioritize both clinical outcomes and economic efficiency. Emerging economic theories such as behavioral economics, which examines how psychological, cognitive, emotional, and social factors influence clinical decisions and patient adherence, and complexity economics, which explores how adaptive behaviors and system interdependencies shape healthcare delivery, are being increasingly analyzed for their potential to improve patient-centered care pathways and reduce inefficiencies [63]. Additionally, dynamic simulation models and system dynamics approaches are now being leveraged to forecast the long-term economic impacts of spine interventions, accounting for patient heterogeneity, treatment variability, and evolving care environments. Quality of life (QOL) measures, such as the EORTC QLQ-C30, QLQ-BN20, and NSCLC-SAQ, have proven invaluable in other fields

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by capturing multidimensional patient-reported outcomes and enriching cost-effectiveness analyses, thus guiding reimbursement decisions, prioritizing interventions that improve both survival and life quality, and supporting personalized care strategies [64–66]. However, spine surgery currently lacks disease-specific QOL instruments that accurately reflect the unique physical, psychological, and functional challenges faced by patients, underscoring the urgent need to develop and validate spine surgery-specific QOL surveys and integrate them into open source databases for large-scale research and precise outcome assessment. Such initiatives would enable more robust economic evaluations, inform clinical decision-making, and facilitate personalized rehabilitation strategies, ultimately advancing both patient-centered care and efficient resource allocation in spine surgery.

Table 1. Overview of AI Applications in Spine Surgery and Diagnostic Workflows. This table categorizes current AI-driven technologies across various domains of spine care, including diagnostic imaging, surgical planning, intraoperative navigation, functional outcome prediction, and economic modeling. Each entry outlines the specific AI tools or systems in use, their validation status, clinical benefits, and known limitations. The table is designed to offer clinicians, researchers, and health policymakers a concise reference for evaluating the maturity, clinical utility, and future development needs of spine-focused AI systems.

AI/ML Application Area	Key Tools/Systems	Validation Status	Clinical Benefit	Limitations
Fracture Detection and Classification	Zebra HealthJOINT, Aidoc Cervical Spine AI	FDA Approved; Real-world validation	Reduced under-detection; Improved triage accuracy	Limited chronic fracture detection; Sensitivity varies
Spinal Segmentation and Grading	SpineNet, Multimodal Segmentation Platforms	External validation across modalities	Automated grading of stenosis, disc degeneration	Performance may vary across demographics
Morphometric Analysis	CobbAngle Pro, Yeh et al. Ensemble Model	Validated vs. clinical experts	Reduced measurement error; Field-applicable	Dependence on image quality
Ultrasound-based Imaging	UGBNet, Attention-UNet	Peer-reviewed feasibility studies	Segmentation of low-contrast images	Noise sensitivity in complex anatomy
Muscle Quality Quantification	CTSpine1K, TrinetX	Open-source annotated datasets	Cross-sectional muscle area & fat infiltration	Need for standardized protocols
Preoperative Planning	Mazor X, ExcelsiusGPS	Clinical integration with robotic systems	Optimized screw trajectory, virtual planning	Variable accuracy in deformed anatomy
Robotic Execution	VELYS, ROSA Spine, Mazor Robotics	FDA-cleared, commercial use	Real-time trajectory correction; Error reduction	Cost and infrastructure requirements
Navigation and Guidance	Brainlab Curve, Medtronic StealthStation	Integrated AI + imaging validation	Adaptive navigation; Improved pedicle accuracy	Setup complexity; Intraoperative variability
Outcome Prediction	GNNs, Transformers, Sentiment NLP	Ongoing studies; Cross-disciplinary use	Predict functional recovery, mental health monitoring	Integration of heterogeneous data types
Cost-Effectiveness and QOL Modeling	Dynamic Simulations, Complexity Economics	Emerging models; Not yet widespread	Forecasting long-term impact; Behavioral insights	Lack of spine-specific QOL instruments

Genomic Applications and Precision Medicine

I. Genome-Wide Association Studies in Spine Surgery Risk Assessment

Recent genome-wide association studies (GWAS) utilizing large biobank datasets, including the UK Biobank and FinnGen, have identified specific genetic loci associated with spinal pathologies and surgical outcomes. A landmark study of 540 surgical adult spinal deformity (ASD) patients revealed 21 significant SNPs linked to surgical risk, with the LDB2 gene variant (rs12913832) shwing the strongest association, implicating ectoderm differentiation pathways in spinal development [67–72]. Concurrently, meta-analyses of lumbar disc herniation (LDH) across three biobanks identified 41 novel loci, including genes involved in inflammation (IL6R), disc structure (COL11A1), and Wnt/β-catenin signaling (DKK1), which regulate spinal biomechanics and degeneration. For lumbar spinal stenosis (LSS), variants near GFPT1 and AAK1 were replicated across cohorts, highlighting roles in glycosylation and synaptic vesicle trafficking that may influence nerve compression [70–74].

Polygenic risk scores (PRS) integrating these variants with clinical variables (e.g., BMI, radiographic severity) now enable preoperative risk stratification, predicting complications like pseudarthrosis (linked to SMAD3 variants) and reoperation [75,76]. Machine learning models, such as those combining GWAS data with radiomics or clinical notes analyzed by large language models [77], improve prediction of neurological deficits and sepsis post-ASD surgery. These tools facilitate early intervention in high-risk patients, such as those carrying CHST3 variants associated with degenerative disc disease, through personalized rehabilitation or biologics targeting dysregulated pathways (e.g., MMP inhibitors for MMP2-associated stenosis).

This integration of genomics into spine care represents a shift toward predictive medicine, with ongoing trials exploring gene-editing (CRISPR-Cas9) and small-molecule therapies to modulate identified targets, such as NFU1 in spinal stenosis and GSDMC in inflammatory disc degeneration [78].

II. Pharmacogenomics and Personalized Pain Management

Pharmacogenomic advancements are also helping spine surgeons with post-op pain management. New findings suggest that key cytochrome P450 variants (CYP2D6, CYP3A4) dictate opioid responses: poor metabolizers (e.g., CYP2D6 null alleles) require larger dose reductions for codeine to avoid inefficacy/toxicity, while ultra-rapid metabolizers risk respiratory depression [79]. AI platforms like PharmCAT and CPIC guidelines integrate this genetic data (e.g., OPRM1 rs1799971 for μ-opioid receptor sensitivity) with EHRs to predict treatment response when given a patient's profile [80–82]. This can also be helpful for clinicians recommending alternatives like tapentadol or non-opioid adjuvants (e.g., duloxetine for COMT Val158Met carriers). For inflammation, IL6 rs1800795 and TNF-α rs1800629 polymorphisms guide NSAID selection, reducing gastrointestinal/renal risks [83]. Postoperative bone healing is optimized via BMP2 rs235768 and VDR rs731236, prompting teriparatide use in high-risk patients [84,85]. New tests like OneOme's RightMed are also beginning to cover progressively more genes in their analysis to understand potential treatment response. Such tests are fortunately making their way into routine post-op assessments and being used prior to medication prescription. Additionally, pain medication prescription following the opioid epidemic that affected many Western countries is gradually improving. Non-addictive alternatives like Gabapentin (targeting calcium channel $\alpha2\delta$ subunits for neuropathic pain) and serotonin-norepinephrine reuptake inhibitors (SNRIs) are increasingly prioritized [86,87].

III. Multi-Omics Analysis

Multi-omics data is also being operationalized through platforms like Seven Bridges Genomics and DNAnexus, which integrate genomics (GWAS/PheWAS), proteomics (Olink's Target 96 Inflammation Panel), metabolomics (Metabolon's HD4 platform), and transcriptomics (10x Genomics' Single-Cell RNA-seq) to map molecular pathways in spinal pathologies [88]. For example, Olink's proximity extension assays have identified elevated IL-6 and COMP (cartilage oligomeric matrix protein) in degenerative disc disease, while Somalogic's SomaScan 7K quantified 7,000 serum proteins linking MMP-3 overexpression to post-surgical pseudarthrosis [89]. Machine learning frameworks like DeepOmics can now predict treatment responses by correlating COL1A1 mutations with collagen dysregulation and ACAN variants with disc hydration loss [90].

Clinical Decision Support and Documentation Systems

I. Ambient Clinical Intelligence and Documentation Automation

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Ambient clinical intelligence systems has transformed documentation workflows, with platforms like Nuance Dragon Ambient eXperience (DAX) and Suki AI offering sophisticated speech recognition and NLP capabilities that generate clinical notes automatically from physician-patient conversations [91]. These systems can effectively diarize conversations, detect significant clinical information, and arrange documents based on specialty-specific templates and guidelines. By integrating these platforms with EHRs, scribes, nurses, and PAs alike can document much more efficiently and accurately.

Notably, specialty-specific charting tools like Ambience Healthcare is another key leap in AI-clinical documentation, with extensive co-pilot capabilities for pre-charting, real-time scribing, and post-visit summary production [92]. The platform's connection with major electronic health record systems allows for bidirectional data transmission and extensive analysis of clinical information, resulting in accurate and thorough documentation. DeepScribe and Notable Health are two other key examples that can be adapted to orthopedics specifically. These systems use deep learning algorithms trained on large spine care datasets to ensure proper detection and recording of spine-specific clinical material. In essence, this training allows them to correct based on spine anatomy and pathology as opposed to purely on grammar or punctuation in dictation. In all, the main reported benefit of these tools is decreased after-hours documentation and labor. In addition to improving work-life balance and lowering the likelihood of provider weariness, these technologies are also used as a check-and-balance to mitigate charting errors. As clinicians supervise the overall algorithm, it allows both parties to ultimately produce accurate chart notes.

II. Clinical Decision Support Systems

Advanced clinical decision support systems incorporating artificial intelligence provide real-time guidance for diagnosis, treatment selection, and management optimization in spine care. IBM Watson for Clinical Decision Support exemplifies the integration of cognitive computing with clinical expertise, analyzing vast amounts of medical literature and patient data to provide evidence-based treatment recommendations [93,94]. These systems can process complex patient presentations and provide differential diagnosis suggestions, treatment options, and prognostic assessments based on current best evidence and individual patient characteristics. The integration of continuous learning capabilities enables these systems to evolve with advancing medical knowledge and incorporate new research findings into clinical recommendations. The integration of multiple data sources including imaging characteristics, patient demographics, comorbidities, and surgical parameters enables comprehensive risk assessment and outcome prediction. Real-time analytics capabilities provide dynamic risk updates based on evolving patient status and intraoperative findings, enabling proactive management strategies that optimize outcomes.

Current Challenges, Limitations, and Implementation Barriers

I. Technical and Algorithmic Limitations

New technological and methodological adoption into routine spine care still faces numerous barriers. Many studies have shown that systems like Aidoc's cervical spine fracture detection and Zebra Medical Vision's HealthJOINT struggle with generalizability across diverse imaging protocols [95,96]. Variations in slice thickness, field of view, and contrast administration cause performance degradation when models encounter unfamiliar datasets [97]. This is unfortunately a reality of imaging, as it is nearly impossible to completely standardize across GE, Siemens, and Philips scanners. Metallic implants, prevalent in revision surgeries, further exacerbate errors, as seen in SpineNet's segmentation failures when processing MRI scans with titanium hardware [98]. This also translates to increased implementation and maintenance costs, as these systems must therefore be constantly monitored and updated.

Additionally, spinal anatomy is complex and there is still more biochemical interactions that are yet to be discovered. Hence, tools like SpineNet begin to grade disc degeneration poorly and quantify spondylolisthesis falters with less common conditions like sacral chordomas [99,100]. This can be

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improved with more representative samples, but sacral chordomas and related tumors often have atypical pathology, structure, and metastatic patterns [101], and it is therefore impractical and implausible that these tools can accurately diagnose all patients. Training datasets can also never be completely accurate, as patient demographics vary dramatically based on geographical language, and type of practice. Hence, many reports have emerged that datasets like CTSpine1K inevitably have underrepresented data. On the other hand, retrospective datasets that are often curated from urban academic centers introduce selection bias, miss rural or underserved patient presentations, and can likewise never be completely representative.

Longitudinal analysis is also important to track disease progression both pre- and postoperatively. Cross-sectional model designs in these various tools can hinder consistent tracking. This is especially harmful for the over 140 U.S. hospitals shuttered since 2010 as well as smaller private practice groups who may not be able to afford the $500,000–$1 million USD price tags of high-performance computing clusters needed for real-time processing [102–104]. Similarly, model interpretability can prevent accurate diagnosis even when AI/ML tools provide accurate reports. This "black box" nature of AI/MLs [105] obscures decision rationale and can fundamentally erode clinician-patient trust over time.

II. Regulatory and Validation Challenges

The FDA's evolving regulatory framework complicates AI deployment in spine care. Continuous learning systems, like those in Mazor X Stealth Edition, challenge traditional validation, as post-market performance shifts unpredictably. As aforementioned, the 2022 study by Chouffani El Fassi et al. noted 226 of 521 FDA-approved AI devices lacked peer-reviewed validation, risking patient safety [10]. Multi-institutional validation, essential for generalizability, is logistically daunting nonetheless; coordinating datasets across rural and urban hospitals can cost $250,000 annually [106] and many clinicians may be resistant to adopt new, often insufficiently tested approaches. The ALIGNMENT study underscores this, showing no significant increase in short-course radiotherapy adoption despite guideline dissemination [107], highlighting validation gaps when protocols vary by institution.

Physician skepticism, rooted in workflow disruption fears, mirrors the ALIGNMENT study's findings, where only 33% of physicians preferred eConsults over colleagues. Similarly, spine surgeons who are accustomed to tactile feedback may resist robotic systems like ExcelsiusGPS. Small practices, facing uncertain reimbursement (Medicare's 2024 cuts reduced spine surgery payments significantly) cannot justify such investments [108]. Regulatory documentation burdens, requiring detailed AI decision logs, add 10–15 hours weekly to administrative tasks, deterring adoption in understaffed clinics.

III. Clinical Integration and Workflow Challenges

Including AI into spine care processes challenges accepted wisdom. Generational differences worsen resistance; older doctors see AI like DeepScribe as compromising autonomy, while younger doctors demand seamless EHR integration [109]. Crucially important but difficult is patient acceptance. Rising data privacy concerns stemming from substantial healthcare data breaches in 2024 make patients cautious of AI/ML tools, including sentiment analysis software.

Table 2. Technical Limitations and Implementation Barriers to Clinical Integration. This table delineates key challenges impeding the widespread adoption of AI in spine diagnostics and surgery, categorized across imaging variability, algorithmic brittleness, dataset bias, explainability deficits, regulatory complexity, infrastructure cost, and clinical integration issues. Each barrier is described with detailed technical considerations and paired with its practical clinical or operational consequence. The table aims to guide researchers, developers, and healthcare administrators in identifying systemic vulnerabilities and prioritizing translational improvements necessary for safe and scalable AI deployment in spinal healthcare.

Category	Barrier	Technical Detail	Clinical/Operational Consequence

Imaging & Model Generalizability	Cross-Vendor Imaging Variability	Heterogeneity in scanner vendor output (e.g., GE vs. Siemens vs. Philips) causes domain shift in AI models; non-uniform slice thickness and FOV distort CNN feature extraction layers.	Decreased classification precision for compression fractures; high false-negative rates in under-standardized imaging environments.
Hardware-Induced Artifacts	Metallic Implant Interference	Titanium-induced susceptibility artifacts in T1/T2 MRI sequences disrupt segmentation accuracy in deep neural networks like SpineNet and V-Net variants.	Invalidated predictions in post-fusion patients; potential for underestimation of central canal and foraminal compromise.
Pathological Heterogeneity	Low Representation of Rare Tumors	Model sensitivity drops when exposed to rare presentations (e.g., sacral chordomas, extradural myxopapillary ependymomas) due to weak class priors and minimal edge-case training data.	False negatives in tumor surveillance; unreliable outputs for oncological follow-up assessments.
Training Data Bias	Geographic and Socioeconomic Overfitting	Training sets skewed toward tertiary care centers cause latent space misalignment for rural/underserved demographics; manifests as calibration drift in diagnostic AI systems.	Inaccurate prioritization in triage algorithms; potential exacerbation of healthcare disparities.
Model Explainability	Opacity in Neural Attribution Maps	Lack of saliency map interpretability or explainable AI (XAI) frameworks in real-time decision support; attention-based models still fall short in spine-specific pathologies.	Limited clinician trust in AI output; inability to validate or refute system recommendations during multidisciplinary rounds.
Infrastructure & Cost	High-Cost HPC Requirements	Inference latency optimization via GPU clusters (e.g., NVIDIA A100) requires capital investment exceeding $500k; suboptimal throughput without federated inference pipelines.	Barriers to adoption in rural and small private clinics; delayed implementation in mid-tier health systems.
Regulatory and Legal Complexity	Validation of Continuous Learning Systems	Regulatory frameworks not equipped for post-deployment model drift; challenge in validating self-updating AI modules under FDA's Good Machine Learning Practice (GMLP) guidelines.	Post-market liability ambiguity; disincentivizes procurement by risk-averse hospital administrators.
Workflow & Physician Engagement	Non-Interoperability with Legacy EHRs	Lack of native HL7/FHIR compliance in AI tools (e.g., DeepScribe); interface incompatibility leads to fragmented data workflows and redundancy in documentation.	Cognitive overload and duplication of work; rejection by high-volume providers.
Patient-Centric Barriers	Privacy Anxiety from Data Breaches	2024 cyberattack exposure of biometric and imaging datasets undermines patient confidence in AI-driven diagnostics; hesitancy persists even with federated learning protocols.	Consent withdrawal and decreased utilization of AI-assisted care; limits scalability of patient-facing applications.

Discussion

The integration of artificial intelligence (AI) and machine learning (ML) into spine care holds transformative promise, redefining diagnostics, surgical precision, and personalized treatment. Tools like automated segmentation systems and robotic surgical platforms enhance clinical accuracy and streamline workflows, while genomic profiling enables tailored risk assessments and pain management strategies. These advancements align with the vision of precision medicine, empowering clinicians to deliver patient-centered care with unprecedented efficiency. Evolving regulatory frameworks, with stricter validation requirements and real-world performance monitoring, foster growing confidence in these technologies. This progress signals a future where AI not only augments clinical decision-making but also bridges gaps in healthcare access, particularly for underserved communities, by leveraging scalable solutions like cloud-based federated learning.

However, significant challenges temper this optimism. Technical limitations, such as difficulties adapting to diverse imaging protocols or handling complex spinal pathologies, highlight the need for more robust and inclusive training datasets. The opaque nature of many AI models risks undermining trust among clinicians and patients, particularly when decision rationales are unclear. Economic barriers further complicate adoption, as high implementation costs and maintenance demands strain smaller practices, while interoperability issues with legacy systems create workflow disruptions. Cultural resistance, driven by concerns over autonomy among seasoned surgeons and patient apprehensions about data privacy, adds another layer of complexity, underscoring the need for transparent communication and education to build acceptance.

Conclusions

Looking forward, a balanced path to AI integration in spine care hinges on collaborative innovation and pragmatic solutions. Streamlined regulatory processes that prioritize rigorous yet efficient validation can accelerate adoption without compromising safety. Partnerships between academic centers, community practices, and industry leaders, modeled on successful collaborative frameworks, can address economic and infrastructural barriers by sharing resources and expertise. By fostering clinician training, patient education, and interoperable platforms, the field can overcome cultural and technical hurdles. The ongoing evolution of regulatory oversight and testing protocols, compared to less stringent earlier standards, offers a hopeful foundation for refining AI tools, ensuring they deliver equitable, precise, and trustworthy care in the years ahead.

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