Review

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Review

Integrating Multi-Modal Predictive Modeling, Imaging Biomarkers, and EHR-Linked Decision Support Systems in Spine-Focused Biomedical Informatics

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Abstract

Spine-focused biomedical informatics has emerged as a critical frontier for applying artificial intelligence (AI) to improve diagnosis, prognosis, and intervention in complex musculoskeletal and neurodegenerative conditions. This review synthesizes recent developments in the integration of machine learning (ML), deep learning (DL), and natural language processing (NLP) within spine health ecosystems. We highlight convolutional neural networks for vertebral segmentation and disc classification, radiomic pipelines for quantitative MRI/CT biomarker extraction, and multimodal ML models for outcome prediction across degenerative, neoplastic, and traumatic pathologies. We examine spine-specific clinical decision support systems (CDSSs) that fuse structured EHR data with NLP-parsed reports, wearable biomechanics, and genomic signals to generate real-time, risk-adaptive treatment guidance. Emphasis is placed on explainable AI (XAI) frameworks—e.g., SHAP, LIME, Grad-CAM—that support interpretability and ethical accountability in AI-augmented decision-making. We analyze challenges in generalizability, privacy-preserving federated learning, and regulatory heterogeneity, with attention to evolving U.S. FDA guidance, EU AI Act obligations, and liability frameworks. Integrating epistemic transparency with computational scalability, this review offers a roadmap for translating AI-enhanced spine informatics into safe, equitable, and clinically trustworthy systems—advancing the goals of biomedical informatics by unifying predictive analytics with ethical and patient-centered care.

Keywords: federated learning; spine; explainable AI; multi-omics; surgical outcomes; NLP; augmented reality; biomechanical wearables

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1. Introduction

Artificial intelligence (AI) is transforming how clinicians diagnose, manage, and monitor spinal disorders [1]. Machine learning (ML) algorithms, particularly deep learning models such as convolutional neural networks (CNNs), now demonstrate high-level performance – and even in some cases, comparable performance to clinicians – in analyzing spinal imaging, automating segmentation, detecting subtle morphological changes, and standardizing diagnostics [2–4]. These technologies are also progressively advancing, with information technology and data analytic groups now increasingly involved in healthcare technology development [5]. Additionally, many clinicians benefit from new knowledge gained around spine anatomy and biomechanical variability, enabling precise, reproducible assessments that improve upon manual methods [6,7]. Radiomics further enhances this capability by extracting quantitative imaging biomarkers from MRI and CT scans, giving clinicians a new set of eyes to stratify surgical risk [8,9].

Simultaneously, natural language processing (NLP) technologies can help analyze unstructured clinical texts—including radiology reports, surgical notes, and EHR narratives—allowing for hospital groups to engage in network-wise analytics and integration with structured data [10,11]. A recent trend has revolved around NLP data mining software that can extract diverse patient information and conduct thorough statistical analyses to detail long-term health trends [12]. AI-enabled clinical decision support systems can similarly generate context-aware, patient-specific recommendations through combining multiple data types [13,14]. Despite these advancements, there are still many real-world implementation hurdles, namely regulatory validation, data privacy, workflow integration, and model explainability [15,16]. In this review, we survey the current landscape of AI applications in spine biomedical informatics, highlighting promising use cases, technical innovations, and translational barriers, while outlining a roadmap for the safe, effective, and equitable deployment of intelligent systems into everyday care [17].

1.1. AI-Powered Imaging Analysis for Spine Health

Surgeons and radiologists alike can mistakenly interpret imaging, especially when evaluating complex structures such as vertebrae, intervertebral discs, and paraspinal muscles [18]. Deep learning models—particularly convolutional neural networks (CNNs)—now allow clinicians to perform high-throughput quantification of vertebral morphology and disc degeneration [19,20]. In doing so, the worldwide spine community benefits from new techniques that can be applied to delineate structures on MRI and CT [21]. Fortunately, many emerging architectures are increasingly being specialized for spine imaging and other bone-related structures [22]. Because the spine and skeletal system have complex, high-resolution anatomical features that general AI models often miss, specialized specialized architectures can help many patients, particularly elderly patients, by detecting subtle abnormalities and biomechanical variations [23,24]. In a similar manner, attention-based CNNs and asymmetric convolution frameworks can focus on key vertebral features and improve segmentation accuracy even in anatomically variable regions [25,26]. MultiResUNet models with saliency-guided localization have been shown to enhance intervertebral disc segmentation by prioritizing relevant tissue regions [27], while patch-based neural networks (e.g., PENN) extract fine-grained features from localized areas to improve structural irregularities (like tumors or excess calcification) [28,29]. Low-complexity CNNs and hybrid pipelines such as VertXNet, have also demonstrated strong performance in radiographic labeling [30]. VertXNet works through ensemble learning and rule-based refinement, whereby it identifies vertebral landmarks and detect alignment issues like spondylolisthesis [31,32]. In parallel, muscle segmentation using CNNs trained on T2-weighted MRI can help physicians objectively assess paraspinal muscle atrophy, which is a critical rehabilitation marker [33,34].

1.2. Radiomics and Imaging Biomarkers in Spine-Focused AI

The primary benefit that AI/ML-integrated radiomics is high-throughput extract of imaging features that cannot be visually inspected, especially intensity distributions, textures, shapes, and spatial arrangements [35,36]. By leveraging open-source platforms like PyRadiomics integrated with 3D Slicer, researchers can extract hundreds to thousands of quantitative descriptors from segmented regions of interest [37]. Vertebral bodies or paraspinal soft tissue can then be analyzed with these descriptors being used as a reference guide [38]. These workflows are also being increasingly automated using deep learning-based segmentation models like U-Net, MultiResUNet, and nnU-Net [39,40]. The main utility here would be for multi-institutional collaboration (i.e. Memorial Sloan Kettering Cancer Alliance, RUSH MD Anderson Cancer Center), where preprocessing and image-derived biomarker generation across diverse datasets and institutions can largely be streamlined [41].

Advanced preprocessing steps—like spatial normalization, landmark calibration, and intensity harmonization—are essential to reduce variability caused by scanner parameters, patient positioning, or anatomical variation [42,43]. For example, vertebral segmentation accuracy can be improved using attention-guided networks or low-complexity patch-based CNNs, such as the PENN framework, which allows effective feature extraction from large volumetric datasets [44,45]. Once standardized, radiomic features are fed into machine learning algorithms for classification and risk stratification [46]. In one important study, CT-derived radiomic signatures more precisely than conventional Hounsfield unit thresholds predicted lumbar spine osteoporosis [47]. ML models trained on T2- and diffusion-weighted MRI have successfully differentiated benign vertebral hemangiomas from metastatic lesions in another study—potentially eliminating the need for invasive biopsies in ambiguous cases, though further testing is needed [48,49]. These applications mirror strategies in genomics, where deep sequencing of conserved and variable regions yields both core diagnostic features and context-specific insights, as in horizontal gene transfer detection or copy number variation mapping [50].

Radiomics growth resides in its ability to generate multimodal predictive models by means of integration with biochemical, genomic, and clinical data [51]. Combining radiomic features with blood-based biomarkers—e.g., plasma cytokine levels, circulating tumor DNA—or multi-omics profiles, for instance, improves prediction of treatment response, progression risk, or postoperative outcomes [52,53]. By allowing repeatable, scalable deployment of AI pipelines combining imaging, EHR, and molecular data, open frameworks like MONAI (Medical Open Network for AI) are helping to enable this convergence [54,55]. This reflects how GWAS incorporate epigenomic signals and gene expression to improve phenotype predictions [56]. Ultimately, radiomic value will be enhanced as it develops from an academic research tool into a clinically useful modality by its capacity to link structural imaging with underlying biochemical processes, thus providing spine specialists with accurate, data-driven tools for personalized, non-invasive diagnostics and risk-adaptive intervention planning [57].

1.3. Data Networks and Open-Source Access

Many global health research network platforms like TriNetX are a primary reason why AI/ML algorithms can have sufficient data to be trained on [58]. For instance, TriNetX provides real-time access to de-identified patient data and advanced analytics, which speeds up the normal timeline that IRB and trial registry would take [59]. TriNetX's Bring Your Own Model (BYOM) feature allows researchers to deploy custom ML models directly onto its extensive real-world data (RWD) network [60]. Spine surgeons can therefore train their models to predict postoperative complications, length of hospital stay, and functional recovery, among other outcomes [61,62]. However, it is still important to access high-quality datasets, regardless of if they are deidentified [63]. Fortunately, many universities are also launching educational programs and data initiatives that equip researchers with relevant health informatics skills and training [64]. For instance, the University of Michigan's AI & Digital Health Innovation program provide researchers with multimodal de-identified health data, including electronic health records, imaging data, and clinical notes [65]. Similarly, the STAnford medicine Research data Repository (STARR) offers extensive de-identified datasets [66].

Explainable artificial intelligence (XAI) models are becoming progressively more important in understanding how ML systems make [67]. By building local surrogate models or computing marginal contribution scores obtained from game theory, model-agnostic interpretation techniques including Shapley Additive Explanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) enable post hoc attribution of model outputs to particular input features [68,69]. SHAP and LIME have been applied to dissect the feature space of gradient-boosted ensembles and deep neural networks in the context of degenerative spinal stenosis and related surgical interventions, thus revealing intraoperative blood loss, age, and comorbidity burden as high-weight contributors to predictive variance [70,71]. In essence, these instruments translate black-box outputs into clinically relevant narratives by quantifying non-linear feature interactions and individualized risk contributions, therein improving model interpretability [72].

1.4. Advancements in Clinical Decision Support Systems for Spine Care

Next-generation clinical decision support systems (CDSSs) today combine structured and unstructured data streams—electronic health records (EHRs), medical imaging, genomic variants, wearable telemetry, and population-scale risk models—into real-time inferential pipelines using multimodal artificial intelligence architectures [73,74]. Using ensemble learning, probabilistic graphical models, and transformer-based architectures, these systems go beyond fixed rule-based logic to provide patient-specific, temporal sensitive recommendations [75,76]. By operationalizing high-dimensional features—e.g., intraoperative neuromonitoring signals, MRI-based morphological signatures, and polygenic risk scores—NeuropredX and SPINE-CALC exemplify this shift for predictive modeling of perioperative complications [77,78].

Knowledge-driven expert systems embedding ontologies and decision rules via forward chaining, classical statistical frameworks leveraging Cox proportional hazards and multivariable logistic regression, and machine learning-based engines using gradient boosting machines, convolutional neural networks (CNNs), and attention-based encoders can be computationally categorized into [79,80]. To process unstructured narratives—e.g., pathology reports, operative notes—modern systems often include pretrained domain-specific NLP models (e.g., BioClinicalBERT), so enabling phenotype enrichment and real-time triage automation [81,82]. Using multimodal inputs—including PROMs, sagittal alignment measures, ASA classification, and spinal marrow signal intensities—prototype systems such as AOSpine's multinational registry-trained platform dynamically stratify patient cohorts [83,84].

Localized interpretability across model architectures is achieved by including explainable AI (XAI) components—SHAP for tabular inference, Grad-CAM for convolutional saliency in imaging, and Integrated Gradients for attribution in NLP pipelines [85,86]. Using SHAP, a pilot system combining diffusion-weighted MRI with paraspinal fat fraction analysis ranked modifiable parameters including sarcopenia index and visceral adiposity in surgical outcome prediction [87]. Federated learning models—such as those developed under the Federated SpineNet project—use frameworks like FedML and Flower to train outcome predictors on distributed datasets without centralizing sensitive data, so obtaining HIPAA-compliant model generalization [88,89]. Using federated averaging with local differential privacy and adaptive weight decay, these models minimize institutional bias and domain shift [90]. Concurrent with integration with external real-world evidence platforms (e.g., TriNetX BYOM, STARR, OHDSI/OMOP CDM), supports retroactive validation and post-market surveillance, so enabling continuous model improvement using worldwide, de-identified EHR corpora [91,92].

Active learning agents that refine risk estimate in response to uncertainty quantification and longitudinal data entry - such as dynamic interval adjustments in tumor surveillance using continuously updated radiogenomic vectors - represent emerging CDSS paradigms [93]. To enable early identification of treatment resistance or metastatic progression, multi-omic frameworks now

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under trial link circulating tumor DNA (ctDNA), MR perfusion parameters, and histologic grade into ensemble prognostic models [94,95]. Even with rapid progress, deployment still faces challenges, namely strong algorithmic governance, high-throughput prospective validation under IRB and regulatory control, and SMART-on-FHIR integration for seamless UI embedding [96,97]. Under research are privacy-preserving machine learning (PPML) techniques including homomorphic encryption, secure multiparty computation (SMPC), and federated differentially private SGD to enable safe multi-site cooperation without violating patient confidentiality [98,99]. Achieving scalable explainability, adaptive learning under covariate shift, and compliance with changing data security standards will ultimately define the evolution of AI-driven CDSSs, ultimately allowing clinicians deploy interpretable, ethical, and clinically translatable decision augmentation tools [100].

1.5. Regulatory Governance, Policy Frameworks, and Legal Translation

This section aims to provide an in-depth legal analysis of the current regulatory landscape in the United States and internationally, focusing on how these frameworks affect spine-specific clinical decision support systems (CDSS), imaging analysis tools, and predictive modeling platforms [101]. It further outlines policy gaps and proposes strategic interventions for lawmakers, regulators, and institutional stakeholders [102].

1. U.S. Regulatory Landscape Under the FDA

AI systems in spine care that meet the definition of a medical device are regulated by the U.S. Food and Drug Administration (FDA) under the authority of the Federal Food, Drug, and Cosmetic Act (FDCA) [103]. Depending on the nature of the AI tool, it may be classified as:

· Class I (low-risk, often exempt from premarket notification),

· Class II (moderate-risk, typically requiring 510(k) clearance), or

· Class III (high-risk, requiring Premarket Approval or PMA) [104].

Most AI-based tools in spine imaging and diagnostics fall under Class II, requiring demonstration of substantial equivalence to a legally marketed predicate device [105]. For example, spine-focused tools like Avicenna.AI's CINA-CSpine and Remedy Logic's RAI MRI analyzer were cleared via the 510(k) process [106]. However, these tools are static—meaning their algorithms do not continuously learn or evolve in the clinical setting [107].

For dynamic models (i.e., continuously learning algorithms), the FDA introduced a framework in 2021 called the Predetermined Change Control Plan (PCCP) [108]. This approach allows developers to pre-specify how a model may evolve post-clearance through algorithmic updates without undergoing new 510(k) submissions [109]. While this framework marks a regulatory breakthrough, it is not yet codified in regulation and remains a nonbinding guidance subject to change under future administrations [110]. The Trump administration's deregulatory posture toward digital health, expressed through the Department of Health and Human Services (HHS) regulatory reform initiatives, may prioritize expedited pathways and greater industry self-certification—potentially weakening post-market surveillance mechanisms [111].

2. Liability and Risk Allocation

Legal liability for AI-related clinical decisions remains poorly defined [112]. Under prevailing tort doctrines, physicians retain primary liability for clinical decisions—even those influenced by FDA-cleared AI tools—unless those tools are mandated for use or represent the standard of care [113]. This creates a paradox: clinicians may face liability for either ignoring or adhering to algorithmic recommendations [114]. Courts have not yet developed a robust framework for allocating blame between AI developers, hospitals, and clinicians in the event of adverse outcomes [115].

The absence of a comprehensive federal AI liability statute in the U.S. means that claims will continue to be litigated under general negligence and medical malpractice standards [116]. Courts are increasingly likely to evaluate whether use of an AI tool aligns with the reasonable physician standard or deviates from customary medical practice [117]. This will hinge on expert testimony, the

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nature of FDA clearance (e.g., predicate-based vs. de novo), and the transparency of the AI's decision-making process [118]. Developers can mitigate liability through robust validation, human-in-the-loop safeguards, and indemnification clauses in commercial licensing agreements [119].

3. Privacy, Security, and Ethical Oversight

AI tools that ingest patient data must comply with the Health Insurance Portability and Accountability Act (HIPAA), particularly in relation to data de-identification, access control, and breach reporting [120]. However, HIPAA was enacted in 1996 and does not address many of the technical realities of AI development, such as federated learning, synthetic data generation, or third-party analytics integration [121].

Given the rise of multi-institutional training networks and clinical research pipelines (e.g., TriNetX, STARR, OHDSI), regulators must clarify how HIPAA applies to nontraditional data use cases [122]. The use of de-identified or limited datasets under a Data Use Agreement (DUA) provides some compliance leeway, but emerging models—such as adaptive CDSS retrained on real-time data—may trigger requirements for patient consent or Institutional Review Board (IRB) approval [123].

Policy options include:

· Creating an AI-specific HIPAA extension to define permissible training, inference, and sharing practices for health data [124];

· Requiring algorithmic impact assessments (AIAs) for spine AI tools integrated into clinical workflows [125];

· Mandating data use transparency portals for patients, similar to data brokers under the California Privacy Rights Act (CPRA) [126].

4. Global Regulatory Divergence: EU, China, and International Trends

The European Union’s Artificial Intelligence Act (AI Act) is poised to become the most comprehensive AI regulatory regime globally [127]. Under the Act, most spine-focused CDSSs and imaging diagnostics would be categorized as high-risk AI systems, subject to conformity assessment, transparency requirements, human oversight, and post-market monitoring [128]. The EU also requires AI systems to comply with the General Data Protection Regulation (GDPR), which imposes consent, data minimization, and the right to explanation under Article 22 [129].

In contrast, China’s Administrative Measures for Algorithmic Recommendation Services (2022) apply cybersecurity and ethical use requirements to healthcare-related algorithms [130]. Developers must register their algorithms with government authorities and undergo security assessments if classified as "important internet services" [131]. This approach is more national-security-oriented and less focused on safety or efficacy [132].

International harmonization remains limited [133]. The International Medical Device Regulators Forum (IMDRF) has issued high-level guidelines on SaMD risk classification, but global interoperability of regulatory approvals remains aspirational [134]. For global spine AI tools, this means developers face fragmented certification processes and clinicians face uncertainty over cross-border liability, especially in telemedicine or remote diagnostics [135].

5. Role of Policymakers and Legal Reform

Policymakers must address the emerging disconnect between AI technological capabilities and the pace of regulatory adaptation [136]. Options include:

· Enacting a Federal Health AI Risk Classification Act, modeled after the EU AI Act, to delineate spine AI tools into low-, moderate-, and high-risk categories with corresponding approval tracks [137];

· Empowering the Office of the National Coordinator for Health Information Technology (ONC) to establish national AI performance benchmarks, especially for diagnostic imaging and predictive modeling [138];

· Expanding the FDA Digital Health Center of Excellence to function as an interagency clearinghouse that liaises with HHS, ONC, NIH, and CMS on AI reimbursement, efficacy, and oversight [139];
· Creating Safe Harbor provisions for clinicians who use validated AI tools in accordance with published clinical guidelines, thus insulating them from liability for good faith reliance on regulated systems [140];
· Requiring AI developers to register tools in a public clinical AI registry, including validation data, intended use, update logs, and known limitations [141].

6. Clinical Translation: What It Means for Providers

For clinicians, these legal developments translate into evolving duties of care, documentation burdens, and medicolegal risk exposure [142]. Surgeons using AI for preoperative planning or intraoperative guidance may need to disclose this during informed consent, particularly if AI use is nonstandard or affects high-stakes decisions [143]. Hospitals must ensure that AI tools are integrated through secure, interoperable systems (e.g., via FHIR standards), and accompanied by ongoing education, auditability protocols, and ethics board review [144].

In addition, spine care providers should:
· Maintain traceable records of AI-derived recommendations and final clinical decisions [145];
· Participate in AI credentialing committees within their institutions [146];
· Advocate for algorithmic explainability in vendor negotiations [147];
· Request indemnification clauses in contracts with AI developers [148];
· Push for malpractice insurance riders that address AI-assisted decision-making [149].

The legal infrastructure governing AI in spine care is rapidly evolving, highly fragmented, and fraught with uncertainty [150]. While FDA guidance and international models provide early blueprints, the legal foundations remain insufficient to ensure safe, equitable, and accountable AI integration in spine medicine [151]. Regulatory convergence, statutory reform, and proactive institutional governance are essential to bridge the gap between innovation and responsibility [152]. Clinicians, developers, policymakers, and legal scholars must work collaboratively to construct a legal ecosystem that empowers innovation while safeguarding the rights, autonomy, and wellbeing of spine care patients worldwide [153].

7. Explainability as a Clinical Imperative in AI-Augmented Care

Integrating AI into spine-oriented clinical decision-making calls for the use of explainable systems to guarantee that model outputs can be clinically relevantly interpreted, evaluated, and used [154]. XAI approaches provide essential utility as artificial intelligence tools are increasingly applied for diagnosis, risk stratification, and surgical planning by clarifying how particular features support model predictions [155]. SHAP, surrogate models, and counterfactuals support the breakdown of complex outputs into recognizable clinical parameters including spinal instability, intraoperative blood loss, and comorbidity indices in spine surgery [156,157]. Especially in high-stakes environments including irreversible interventions, these techniques help providers evaluate the alignment of model outputs with anatomical reasoning and established guidelines [158].

XAI also improves consistency in settings of multidisciplinary treatment [159]. Accessible explanations help to lower the risk of uncritical reliance on AI outputs and encourage fair participation in decision-making when predictive tools are applied throughout hierarchies involving surgeons, trainees, and non-physician clinicians [160]. Interpretability helps institutional quality assurance initiatives including audits for model drift, performance evaluation across subgroups, and feature stability over time [161]. In models generating probabilistic outputs, a fundamental need is uncertainty communication [162]. Decisions involving spines are often sensitive to small variations in expected risk, thus outputs should be supported by information on data limits, confidence intervals, and calibration data [163]. Appropriate context helps to prevent misinterpretation of risk estimates or excessive influence in common decision-making [164].

Generalizability still depends critically on training data variability [165]. XAI lets doctors find possible bias related to demographic imbalance, imaging heterogeneity, or institutional differences by means of mechanisms for evaluating how input features behave across various populations [166]. In federated learning environments and multi-center partnerships, where harmonization of data inputs may not completely offset underlying biases, these features are especially critical [167]. Interoperability with external data platforms including TriNetX, OHDSI, and institutional registries highlights even more the need of interpretability [168]. Local model validation can be enhanced by attention-based NLP models, saliency maps for imaging, and temporal attribution tools for EHR time series data, enabling suitable use of AI tools in many different care environments [169,170].

Explainability is, all things considered, a functional need for artificial intelligence application in spine care [171]. Transparency, support of clinical validation, and guaranteed interpretability and actionability of model outputs within current care systems are made possible by XAI approaches [172]. Integration of XAI will be crucial to keep clinical dependability, regulatory alignment, and ethical responsibility as artificial intelligence applications keep growing [173].

8. Discussion

Measurable performance improvements have been shown by applications ranging from automated vertebral segmentation and radiomics-based risk stratification to NLP Huntington Beach (CA) Airport (LAX) Airport, ranging from automated vertebral segmentation and radiomics-based risk stratification to NLP-enhanced operative note analysis [174]. Still, many technical, legal, and clinical constraints restrict the shift from research prototypes to clinically integrated decision tools [175].

Current models primarily depend on retrospective, often single-institutional datasets that might not fully reflect the heterogeneity of spine pathology or practice variation across care settings [176]. Imaging modalities, surgical technique, or documentation methods can all affect predictive performance in external cohorts, and while federated learning and transfer learning can help mitigate this risk, they may compromise differential privacy compliance, version control, and model coordination [177,178]. Furthermore, the degree of interpretability needed for regular clinical integration has not been consistently defined even if XAI approaches including SHAP, Grad-CAM, and counterfactual reasoning help to improve model interpretability [179]. Particularly when models span multimodal inputs, feature attribution by itself may not be enough to support informed clinical decision-making [180]. The difficulty thus resides not only in determining varying importance but also in matching these outputs with accepted clinical heuristics, causal reasoning models, and guideline-concordant thresholds [181]. Without this, clinicians risk overdependence on technically sound forecasts without enough background to support tailored patient treatment [182].

Moreover, operational deployment brings problems with workflow [183]. Real-time integration into surgical planning systems or EHR systems calls for consistency in latency performance, security data exchange protocols, and interoperability standards including SMART-on-FHIR [184]. Many artificial intelligence tools nowadays lack this kind of integration, which leads to inconsistent user experiences or inadequate acceptance [185]. Moreover, clinician participation in post-deployment audits and development still is rather limited [186]. Models may suffer from drift or silent failure modes undetectable until negative events happen without continuous recalibration depending on user feedback and outcome tracking [187].

FDA guidance—especially with reference to the AI/ML-Based SaMD Action Plan and PCCPs—is also still adapting and lacks consistent proscription [188]. Global regulatory harmonization is still in its infancy even if the European Union's AI Act provides more prescriptive criteria for high-risk medical applications [189]. Liability for negative effects connected to artificial intelligence use—especially in cases when the clinician depends on a validated but opaque system—remains unresolved [190]. When artificial intelligence systems help to make medical decisions, institutions have to start building transparent systems for responsible allocation of resources, version documentation, and informed consent processes [191]. Patient communication ethically still presents a difficult task [192]. Patients are entitled to know how clinical decisions are made even if they are not expected to interpret algorithmic outputs—especially when systems trained on outside datasets shape recommendations [193]. Neither a current standard for reporting AI involvement in decision-making nor for recording whether the use of such systems changes long-term management strategies, risk-benefit assessments, or surgical thresholds [194].

Ultimately, the possibility of autonomous artificial intelligence for treatment planning or spine diagnosis stays hypothetical [195]. Although present systems have great augmentation power, they lack the contextual awareness, generalizability, and explainability required to run free from clinical control [196]. High-stakes spine surgery applications—where hazards include paralysis, infection, and long-term disability—demand that final decisions remain under human clinical authority, supported but not mandated by algorithmic inference [197].

9. Conclusions

AI continues to reshape the field of spine-focused biomedical informatics through its capacity to analyze complex, multimodal datasets, enhance diagnostic throughput, and generate predictive insights with increasing granularity [198]. From image segmentation to postoperative outcome forecasting, a wide range of models and techniques have demonstrated strong potential for clinical augmentation [199].

However, substantial limitations remain [200]. Model generalizability across diverse clinical environments, standardization of interpretability frameworks, real-time deployment infrastructure, and clearly defined legal accountability structures are all incomplete. The current generation of AI systems is best understood as decision support tools—not autonomous clinical agents. To achieve reliable integration into spine care, AI systems must incorporate robust XAI methods, accommodate site-specific variability, provide mechanisms for transparent communication of uncertainty, and remain compatible with clinical reasoning processes. These systems must also adhere to regulatory and ethical standards that protect patient safety, preserve clinical judgment, and support equitable care delivery.

Future research should focus on prospective validation, real-world deployment studies, and clinician-centered model refinement. Cross-institutional collaborations using federated learning and harmonized data ontologies may support the development of more robust, generalizable models. At the same time, clinical institutions must invest in AI literacy, model governance, and infrastructure readiness to ensure responsible adoption. In all, while AI holds transformative potential for spine care, its safe and effective use depends on rigorous interpretability, institutional oversight, and sustained clinical engagement. Progress toward automation should be measured, transparent, and grounded in the core values of clinical integrity, accountability, and patient-centered care.

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