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Review

Transition to Artificial Intelligence in Imaging and Laboratory Diagnostics in Rheumatology

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Abstract

Artificial intelligence (AI) is rapidly transforming rheumatology, particularly in imaging and laboratory diagnostics where data complexity challenges traditional interpretation. This narrative review summarizes current evidence on AI-driven tools across musculoskeletal ultrasound, radiography, MRI, CT, capillaroscopy, and laboratory analytics. A structured literature search (PubMed, Scopus, Web of Science; 2020–2025) identified 90 relevant publications addressing AI applications in diagnostic imaging and biomarker analysis in rheumatic diseases, while twelve supplementary articles were incorporated to provide contextual depth and support conceptual framing. Deep learning models, notably convolutional neural networks and vision transformers, have demonstrated expert-level accuracy in detecting synovitis, bone marrow edema, erosions, and interstitial lung disease, as well as in quantifying microvascular and structural damage. In laboratory diagnostics, AI enhances the integration of traditional biomarkers with high-throughput omics, automates serologic interpretation, and supports molecular and proteomic biomarker discovery. Multi-omics and explainable AI platforms increasingly enable precision diagnostics and personalized risk stratification. Despite promising performance, widespread implementation is constrained by significant domain-specific validation gaps, data heterogeneity, lack of external validation, ethical concerns, and limited workflow integration. Clinically meaningful progress will depend on transparent, validated, and interoperable AI systems supported by robust data governance and clinician education. The transition from concept to clinic is under way—AI will likely serve as an augmenting rather than replacing partner, standardizing interpretation, accelerating decision-making, and ultimately facilitating precision, data-driven rheumatologic care.

Keywords: artificial intelligence; rheumatology; diagnostic imaging; biomarkers; clinical decision support systems

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1. Introduction

The field of rheumatology is undergoing a transformative shift driven by the growing complexity of data derived from advanced imaging modalities, laboratory assays, and

multi-omics technologies [1,2]. Traditionally reliant on expert clinical judgment and pattern recognition, rheumatic disease diagnosis and monitoring increasingly require the interpretation of large volumes of heterogeneous data [3]. This evolution creates both opportunities and challenges—necessitating tools that can process, integrate, and learn from complex datasets to support accurate and timely clinical decision-making. Moreover, the emergence of ethical concerns has outpaced the development of comprehensive global legislation, which remains insufficient to address the complexities of AI integration in healthcare and in particular rheumatology [4].

Artificial intelligence (AI), particularly in the form of machine learning (ML) and deep learning (DL), offers promising solutions to these challenges. In imaging diagnostics, AI algorithms can enhance image acquisition [5], automate interpretation [6], and support quantification of structural and inflammatory lesions with high precision [7]. These capabilities can reduce inter-observer variability, accelerate workflows, and potentially uncover imaging patterns not readily discernible to the human eye [8,9]. Similarly, in the domain of laboratory diagnostics, AI enables the integration of conventional biomarkers with high-throughput omics data (genomics, transcriptomics, proteomics), promoting a transition toward precision medicine [10].

Despite growing interest and promising pilot studies, the adoption of AI in routine rheumatology practice remains limited. Barriers include technical complexity, lack of validation in diverse populations, concerns about transparency (the so-called "black box" effect) [1], and limited integration into clinical workflows. A clear understanding of current capabilities, evidence, limitations, and implementation pathways is essential to move from proof-of-concept studies to real-world clinical utility [4].

This data-rich environment raises key questions: How can AI models be reliably applied to these heterogeneous data? What is the current evidence for their accuracy in specific diagnostic tasks, and what barriers prevent their routine use? By synthesizing the available evidence and identifying knowledge gaps, this review aims to serve as a resource for clinicians, researchers, and healthcare planners interested in the transition toward AI-supported rheumatologic care.

2. Materials and Methods

In accordance with the principles of high-quality narrative reviews outlined by Gasparyan et al. [11], we conducted a structured literature search to gather and synthesize current evidence on the transition towards AI in imaging and laboratory diagnostics within rheumatology.

2.1. Databases and Sources Consulted

To ensure a comprehensive and interdisciplinary overview, we systematically searched the following databases: PubMed/MEDLINE, Scopus, Web of Science. These databases were chosen to encompass both clinical and technical aspects of AI application in rheumatology, including diagnostic imaging and laboratory data processing. Additionally, Google Scholar was consulted to identify grey literature, preprints, and citation patterns not indexed elsewhere. The reference lists of included articles and relevant systematic reviews were manually screened to capture additional sources.

2.2. Search Terms and Boolean Strategy

The search strategy combined free-text terms and Medical Subject Headings (MeSH) related to AI, diagnostic technologies, and rheumatologic conditions. The following Boolean logic was applied and tailored to each database syntax ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("rheumatology" OR "rheumatoid arthritis" OR

"spondyloarthritis" OR "arthritis") AND (("imaging" OR "ultrasound" OR "MRI" OR "radiographs") OR ("laboratory" OR "biomarkers")).

The search was iterative and adjusted based on initial findings to capture relevant subtopics such as lesion quantification, automated scoring systems, and AI-supported interpretation tools.

2.3. Inclusion and Exclusion Criteria

Studies were considered eligible if they focused on the use of AI in diagnostic imaging (e.g., musculoskeletal ultrasound, MRI, radiography) or laboratory diagnostics (e.g., automated biomarker interpretation) in rheumatic diseases and were original research articles or high-quality abstracts with detailed methodology, preprints (lack of data from peer-reviewed articles), narrative, or systematic reviews.

We excluded studies unrelated to rheumatology, reports solely discussing therapeutic applications of AI, papers without clinical relevance (e.g., technical algorithm development with no human validation), editorials, letters, and conference abstracts lacking detailed methodology or results.

2.4. Study Selection Flow

To reflect the contemporary developments in AI, we limited the search to publications from January 2020 to June 2025. Only articles published in English were considered, as translations may not consistently reflect scientific accuracy and are rarely peer-reviewed. A structured literature search across PubMed, Scopus, Web of Science yielded a total of 2651 records. After removal of duplicates and normalization of titles, 1873 unique records remained. Based on predefined inclusion criteria emphasizing relevance to AI applications in imaging and laboratory diagnostics within rheumatologic conditions, 90 studies were included in the final synthesis. In addition, twelve supplementary articles were incorporated to provide contextual depth and support conceptual framing. This process ensured comprehensive coverage of the interdisciplinary literature while maintaining a focus on clinically and technologically relevant content. Findings were summarized thematically across overview of AI, imaging modalities, laboratory domains, and AI architectures.

Findings were summarized thematically. The subsequent review is structured as follows: Section 3 provides a foundational overview of AI in medicine. Section 4 delves into AI applications across key imaging modalities in rheumatology (Musculoskeletal ultrasound, MRI/CT, radiography, and capillaroscopy). Section 5 explores the role of AI in laboratory diagnostics and biomarkers. Finally, Section 6 discusses the integration of these tools into clinical decision support systems.

3. Overview of Artificial Intelligence in Medicine

The integration of AI is transforming healthcare, from fundamental research to clinical practice [12]. The evolution of AI's subfields, ML and DL, provides powerful tools for data analysis, diagnostics, and operational optimization. However, this technological shift requires careful navigation of a complex and evolving landscape of regulatory and ethical considerations [13].

3.1. Foundational Definitions: AI, ML, and DL

Artificial intelligence is a broad field of computer science dedicated to creating systems that simulate human intelligence, such as problem-solving and learning [14]. Within a medical context, AI refers to computational programs that use algorithms to process raw data and inform clinical decisions. A key subset, ML, enables systems to learn from data and identify patterns without being explicitly programmed [15]. This data-driven process differs fundamentally from older, rule-based AI. ML models are typically categorized as

supervised, unsupervised, or reinforcement learning [14].Figure 1 illustrates the evolution of artificial intelligence over the decades, highlighting milestones relevant to medical imaging, laboratory diagnostics, and rheumatology.

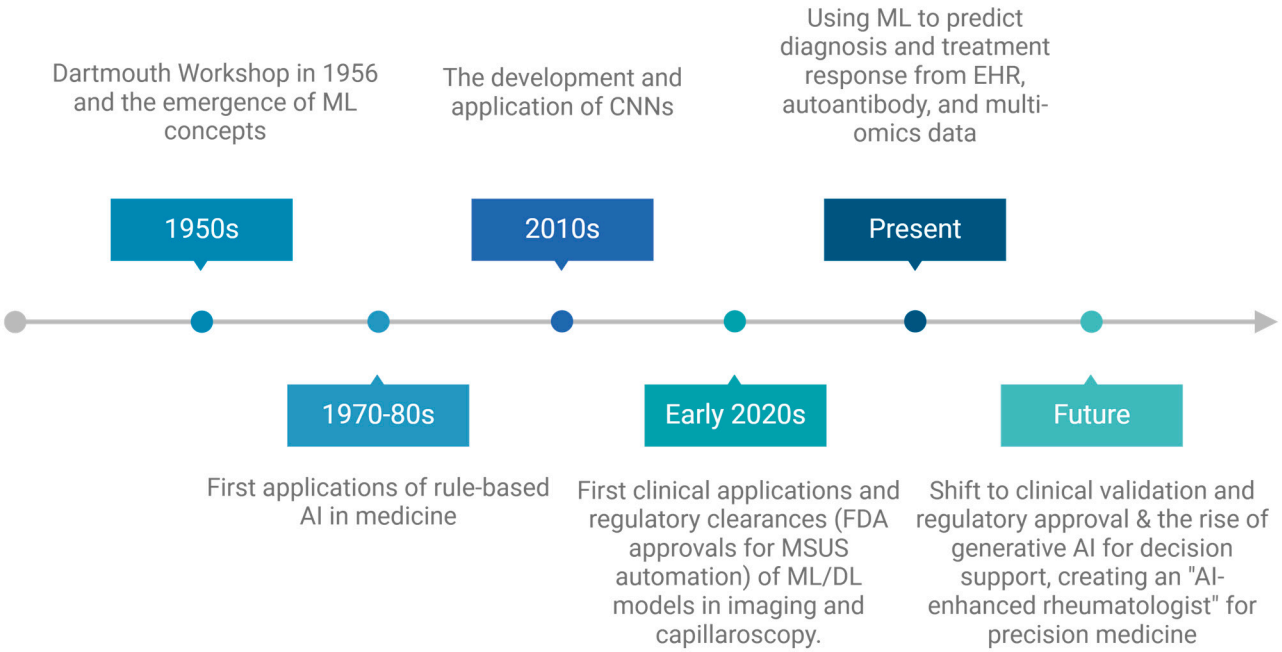

Figure 1. Timeline of Artificial Intelligence Development in Rheumatology.

Deep learning, a specialized form of ML, has driven many of AI's recent breakthroughs [16]. DL employs complex, multi-layered artificial neural networks (ANNs) to analyze large volumes of unstructured data, such as medical images or clinical text, where traditional ML methods may be less effective [17]. For instance, Convolutional Neural Networks (CNNs), a type of DL model, are exceptionally effective in computer vision tasks involving radiographs and CT scans [15]. While powerful, the complexity of DL models can present challenges related to interpretability [16].

3.2. Current Applications in the Healthcare Ecosystem

AI applications in medicine are expanding rapidly. In diagnostics and prognosis, DL models demonstrate high accuracy in analyzing medical images, enabling earlier and more precise disease detection [13]. Clinical decision support systems also use patient-reported data to generate differential diagnoses [18]. AI is a cornerstone of personalized medicine, where algorithms analyze vast biological and genomic datasets to tailor treatment strategies and accelerate drug discovery [16,18].

Operationally, AI optimizes clinical workflows by automating administrative tasks like scheduling and billing, and by assisting clinicians with transcribing consultations directly into electronic health records (EHRs), reducing administrative burdens [16,18]. AI also enhances patient engagement and monitoring through virtual health assistants and wearable devices that facilitate proactive management of chronic diseases [13,16].

3.3. Regulatory and Ethical Perspectives

The rapid integration of AI into healthcare necessitates robust ethical and regulatory oversight, a framework that often evolves reactively to technological advancements [19]. While reporting guidelines like CONSORT-AI and SPIRIT-AI have been developed to promote transparency in research, their practical application remains a challenge [20].

The ethical discourse is anchored in the core principles of biomedical ethics [21]. Key concerns include the protection of patient privacy and data security to comply with regulations like HIPAA and GDPR [21]. A significant risk is algorithmic bias, where models trained on unrepresentative data can amplify existing health disparities [16]. The opaque nature of some DL models—the "black box" problem—creates challenges for transparency and accountability, complicating the assignment of responsibility for AI-driven outcomes [19]. Ultimately, building clinician and patient trust is paramount and depends on addressing these concerns about security, fairness, and the need for meaningful human oversight in all AI-assisted medical decisions [22].

4. AI in Imaging Diagnostics in Rheumatology

4.1. Musculoskeletal Ultrasound

Musculoskeletal ultrasound (MSUS) is a cornerstone of modern rheumatological practice, offering real-time, dynamic imaging of joints, tendons, and other soft tissues without the use of ionizing radiation [23,24]. It is highly valuable for diagnosing and monitoring inflammatory conditions, particularly in assessing synovitis, which is a key feature of diseases like rheumatoid arthritis (RA) [23,25]. However, the utility of MSUS is constrained by its significant operator dependency, leading to variability in both image acquisition and interpretation, which can affect diagnostic accuracy and consistency in multicenter clinical trials [23,25,26]. The interpretation of findings, especially the semi-quantitative scoring of synovitis, is often time-consuming and subject to considerable inter- and intra-observer variability, even among experienced sonographers [23,25,27].

AI, particularly through ML and DL models, presents a transformative solution to these challenges [23]. AI-based systems have the potential to standardize image analysis, improve accuracy, reduce variability, and enhance workflow efficiency [23,24]. These algorithms can automate tasks such as tissue recognition, segmentation of anatomical structures, and the classification and grading of pathology, thereby providing a consistent, objective "second opinion" to the clinician [23,26].

A primary application of AI in MSUS is the automated assessment of synovitis. The European Alliance of Associations for Rheumatology (EULAR) and the Outcome Measures in Rheumatology (OMERACT) group have developed a standardized scoring system for synovitis (EOSS) that evaluates synovial hypertrophy (SH) in grey-scale (GS) and vascularity using Power Doppler (PD) or Color Doppler (CD) on a 0–3 scale [25,28]. Several studies have successfully developed and tested AI models, predominantly based on convolutional neural network (CNN) architectures, to automate this scoring process. For instance, Andersen et al. demonstrated that CNNs could classify Doppler ultrasound images as healthy/diseased with high accuracy (over 86%) and grade them according to the full OESS scale with a quadratically weighted kappa score of 0.84, indicating strong agreement with an expert rheumatologist [27]. Building on this, Christensen et al. (2020) introduced a more advanced cascaded CNN design that further improved the four-class accuracy to 83.9% and showed no significant difference from expert assessment on a per-patient level [26]. He et al. (2024) [25] expanded this research by developing DL models for multimodal US data, including both static and dynamic GS and PD images [25]. Their findings indicated that dynamic models, particularly the dynamic power Doppler (DPD) model, often outperformed static models and were more accurate than most senior radiologists, suggesting that incorporating temporal information from video clips enhances diagnostic capability [25].

Beyond synovitis, AI models have shown promise in evaluating other musculoskeletal pathologies. Computer-aided diagnosis (CAD) systems have been developed for the automated recognition of supraspinatus tendinopathy and the detection of calcifications with reported accuracies exceeding 90% [23]. Furthermore, AI has been applied to cartilage

assessment, a key component in osteoarthritis (OA) evaluation. DL models based on the U-Net architecture have been effectively used for automated cartilage segmentation in volumetric US images, which is critical for measuring cartilage thickness and monitoring degenerative changes. These automated techniques show promising results when validated against manual delineations and have potential applications in the early detection of OA and even in assisting robotic knee arthroscopy [23,24,29].

However, the performance of these AI models often remains dependent on standardized image acquisition protocols, and their robustness against real-world image quality variability and differences in probe positioning requires further validation.

4.2. Magnetic Resonance Imaging and Computed Tomography

Computed tomography (CT) and magnetic resonance imaging (MRI) are cornerstone diagnostic tools in rheumatology. CT, with advanced applications like dual-energy (DECT) and high-resolution (HRCT), is pivotal for assessing structural bone changes, quantifying monosodium urate crystals in gout, and evaluating interstitial lung disease [30]. MRI provides superior sensitivity for early inflammatory markers such as bone marrow edema and synovitis, making it invaluable for diagnosing and monitoring inflammatory arthritides [31]. Furthermore, AI, particularly deep learning, is enhancing the very acquisition process of MRI itself. By learning to reconstruct high-fidelity images from significantly undersampled raw data, AI techniques can dramatically reduce scan times while preserving diagnostic quality. This acceleration addresses a key limitation of MRI, improving patient experience and potentially allowing for more widespread or frequent use in monitoring rheumatologic conditions [32].

However, manual interpretation is time-consuming, expertise-dependent, and prone to observer variability. To address these limitations, AI enables automated and objective scoring systems. This AI-driven analysis enhances the detection of key pathological features, promising a more efficient and precise approach to rheumatologic disease management [33].

Recent advancements in AI, particularly deep learning, are poised to transform diagnostic imaging in rheumatology. In the realm of spondyloarthropathies (SpA), where imaging plays a central yet complex role, a systematic review highlighted the high diagnostic accuracy of algorithms like convolutional neural networks (CNNs) across MRI, CT, and X-ray modalities, with some models achieving performance comparable to expert radiologists [34]. This diagnostic potential is exemplified in a randomized controlled trial that developed an automated machine learning model using sacroiliac joint MRI, which demonstrated excellent performance in identifying early sacroiliitis [35].

Beyond initial diagnosis, AI is also revolutionizing the quantitative assessment of disease activity. For instance, one study found that machine learning-based software for scoring bone marrow edema (BME) in spinal MRI performed comparably to expert raters but with enhanced consistency and reduced inter-reader variability [36]. Similarly, a pre-trained deep learning algorithm was validated and proved reliable in detecting inflammatory lesions in sacroiliac joint MRIs according to established ASAS criteria, further underscoring the potential for automated, standardized disease monitoring [37].

The application of AI extends from inflammatory arthropathies to degenerative conditions like osteoarthritis (OA). A systematic review assessed the use of AI in automating MRI scoring for knee arthritis, noting that while certain biomarkers like effusions were readily automated, others such as cartilage loss remained challenging to quantify accurately [38]. Despite these challenges, significant progress is being made; for example, a fully automated, T2-mapping-based method for cartilage analysis was successfully evaluated and showed high agreement with manual expert analysis, supporting its utility in early OA detection [39].

AI's impact is not confined to musculoskeletal imaging; it is also proving crucial for assessing systemic manifestations such as interstitial lung disease (ILD) in patients with connective tissue disease (CTD). An observational study utilizing AI-enhanced HRCT revealed that a significant number of asymptomatic CTD patients already had imaging evidence of ILD, emphasizing the need for early, risk-adapted screening [40]. Reinforcing the reliability of this technology, another study demonstrated the feasibility of fully automated CT scoring for ILD, where AI-derived heatmaps closely matched expert assessments, thereby enhancing diagnostic accuracy and transparency [41].

The versatility of these computational methods is further demonstrated in other domains of rheumatology. Research has shown that combining clinical risk factors with radiomics data from quantitative CT can create a powerful tool for diagnosing osteopenia and osteoporosis [42]. In the field of idiopathic inflammatory myopathies, machine learning-based texture analysis of muscle MRI has been shown to non-invasively help predict disease subtypes and autoantibody profiles, offering valuable insights into disease mechanisms [43].

4.3. Conventional Radiography

Conventional radiography remains the cornerstone for assessing structural joint damage in RA, SpA, osteoarthritis, and related conditions. Erosions and joint space narrowing (JSN) are key radiographic features reflecting disease severity and progression, and their quantification through established scoring systems such as the Sharp/van der Heijde (SvH) or the modified total Sharp score (mTSS) is central to both clinical trials and long-term patient management [44]. However, manual scoring is time-consuming, requires substantial expertise, and is limited by inter- and intra-observer variability. These challenges have prompted increasing interest in AI solutions for automated image interpretation.

Recent years have witnessed remarkable progress in the application of deep learning methods to radiographic assessment in RA. Convolutional neural networks (CNNs) and vision transformers (ViTs) have been trained on large annotated datasets to automatically detect erosions and JSN with performance approaching or exceeding expert readers. For example, Venäläinen et al. developed the AuRA algorithm, capable of predicting SvH scores and monitoring progression with high accuracy in external validation cohorts, showing significant correlation with expert-assessed progression and improved robustness in patients with severe disease [44,45]. Similarly, Moradmand et al. (2025) proposed a multistage framework combining U-Net-based segmentation, YOLOv7 joint detection, and ViT-based score prediction, achieving almost 99% accuracy in joint identification and good correlation with expert scoring at lower damage levels [45,46].

Several studies have focused specifically on automated radiographic progression scoring. Bird et al. tested AI-based systems for automated SvH scoring across external cohorts and found that while relative ranking of patients was feasible, absolute agreement with expert scorers remained low (ICC 0.03–0.27), highlighting ongoing limitations [47]. By contrast, Bo, Coates and Papiez demonstrated that deep learning pipelines without explicit joint localization could predict total SvH scores directly from hand radiographs, achieving high correlation with expert assessments (PCC up to 0.925) [48]. Other approaches have emphasized joint-level precision: Fung et al. combined YOLOv5 and CNN models for joint detection and lesion scoring, reporting promising results in erosion and JSN quantification during the RA2-DREAM challenge [49].

Recent methodological advances include the incorporation of attention mechanisms to improve interpretability and performance. Lien et al. showed that U-Net combined with EfficientNet and attention modules yielded substantial agreement with human scorers for erosion and JSN ($\kappa \approx 0.86$–0.88), supporting its potential utility in clinical and research settings [49]. Beyond classification and scoring, Wang et al. proposed a registration-

based deep learning method for quantifying JSN progression through intra-subject image alignment, enabling highly accurate subpixel measurements of change over time [50].

Taken together, these studies demonstrate that AI has the potential to standardize and accelerate radiographic assessment, reduce observer bias, and enable large-scale, reproducible evaluation of structural outcomes in RA. While early evidence suggests AI may complement human expertise by enhancing sensitivity to subtle changes and providing consistent scoring, significant challenges remain, including the need for diverse and high-quality training datasets, rigorous external validation, and clear regulatory frameworks. As summarized in a recent review by Sun et al., the transition towards AI in rheumatology imaging holds promise for earlier detection of damage and more personalized therapeutic strategies [51], but widespread clinical adoption will depend on addressing these methodological and implementation barriers [52].

4.4. AI in Capillaroscopic Diagnostics

4.4.1. The Clinical Challenge: Subjectivity and Accessibility in Capillaroscopy

Nailfold videocapillaroscopy is the established gold standard for visualizing the microcirculation at the nailfold, playing a critical role in differentiating benign primary Raynaud's phenomenon from secondary Raynaud's phenomenon associated with an underlying connective tissue disease [53]. The presence of abnormal capillaries—such as giant capillaries, microhemorrhages, and capillary loss—is a key finding that contributes directly to the American College of Rheumatology/European Alliance of Associations for Rheumatology (ACR/EULAR) classification criteria for SSc [54].

Despite its diagnostic importance, the widespread clinical utility of NVC is significantly hampered by two fundamental challenges. First, the interpretation of NVC images is a time-consuming process that is highly dependent on the experience of the examiner [55]. This leads to considerable inter-observer and intra-observer variability in the assessment of capillary morphology, making it difficult to standardize results and compare findings across different studies or clinical centers [56]. Even among experienced capillaroscopists, agreement on the classification of abnormalities can be inconsistent [57]. Second, there is a significant barrier to access. Many rheumatology clinics, particularly outside of large tertiary centers, lack the specialized, often expensive, equipment and the trained personnel required to perform and interpret NVC examinations effectively [58].

4.4.2. AI-Powered Quantitative Analysis: A Shift Towards Objectivity

Artificial intelligence, powered by both machine learning and deep learning algorithms, offers a compelling solution to the challenges of subjectivity and accessibility in NVC. AI-driven systems are capable of performing fully automated, objective, and quantitative analysis of NVC images, transforming a qualitative assessment into a data-driven one [59].

These automated systems are designed to detect, segment, and measure a wide array of morphological features from NVC images. They can quantify capillary density, measure capillary width and apical diameter, identify abnormal shapes and tortuosity, and detect specific pathological features such as giant capillaries and microhemorrhages with high precision [59]. The overarching goal is to provide rheumatologists with an objective and reliable decision-support tool that can be used at the point-of-care [60]. By automating the analysis, these tools drastically reduce the time required for interpretation—from over 15 minutes per patient for manual assessment to just seconds or minutes—while simultaneously eliminating examiner-related bias [61]. This technological advancement not only enhances diagnostic consistency but also has the potential to democratize the use of NVC, making its benefits more widely available.

4.4.3. Key AI Models and Their Performance

In recent years, a variety of AI-powered models for NVC analysis have been developed and validated, with many demonstrating performance that is comparable or even superior to the consensus of human experts [55,59,62]. The field is maturing rapidly, with a clear trajectory from simple classification tasks toward more nuanced quantification and prediction. This evolution is evident in the progression from rule-based algorithms to sophisticated machine learning and deep learning systems. Furthermore, a key focus of this research has been the validation of these tools on images acquired from low-cost, accessible devices, directly addressing the equipment barrier that has limited NVC adoption [58,59].

A number of distinct models have emerged (Table 1), each with specific architectures and clinical applications:

- CAPI-Score and CAPI-Detect: The CAPI-Score algorithm was an important early effort to standardize NVC interpretation using a set of simple, quantitative rules inspired by expert consensus [63]. Its successor, CAPI-Detect, represents a significant leap forward. It employs a machine learning model (CatBoost) trained on a large dataset of expert-annotated capillaroscopies and integrates 24 distinct quantitative variables related to capillary architecture [59]. CAPI-Detect significantly outperforms its predecessor, achieving accuracy rates exceeding 90% for distinguishing SSc from non-SSc patterns and over 92% for correctly staging SSc (early, active, or late), particularly when validated against cases with full expert consensus [59]. A key feature is its ability to provide probability scores for each potential pattern, offering a more nuanced output that reflects the model's confidence [63].
- Deep Learning Systems (ResNet, ViT, and others): Other research groups have focused on deep learning architectures. A pilot study utilized a ResNet-34 deep residual neural network to classify NVC images as normal or pathological, reporting a sensitivity of 89.0% and a specificity of 86.9% on its validation set, along with a high precision of 96.48% for automated capillary counting [55]. Another fully automated system, developed at the University of Manchester, used deep learning networks to mimic the interpretation strategies of experts. It achieved an area under the receiver operating characteristic curve (AUC) of 97% for identifying SSc, a performance that exceeded the reported 82% sensitivity and 73% specificity of expert consensus [60]. This system was notably validated on images from both high-resolution systems and low-cost USB microscopes, demonstrating its robustness [64]. More recently, the Vision Transformer (ViT) architecture has been applied, showing strong performance in identifying specific microangiopathic changes like giant capillaries (AUC 92.6%) and enlarged capillaries (AUC 90.2%) [65].
- ARTIX (AI-based Raynaud's Quantification Index): Moving beyond diagnosis, the ARTIX tool leverages AI to provide an objective, quantitative measure of Raynaud's phenomenon (RP) severity directly from photographs taken with a standard mobile phone [62]. In a validation study comparing its output to thermography during a standardized cold challenge, ARTIX successfully discriminated between patients with RP and healthy controls ($p < 0.001$) and showed correlations with clinical features [62]. This innovation points toward a future of patient-centered, remote monitoring of disease activity.

While some systems (like the Manchester System) have demonstrated robustness on low-cost devices, a formal comparative analysis of scalability for other leading models (e.g., CAPI-Detect) across the full spectrum of hardware (from high-end systems to low-cost USB scopes) is lacking and crucial for primary care implementation.

Table 1. A comparative summary of the leading AI models is provided, highlighting their diverse approaches and applications. This synthesis allows for a direct comparison of their technological underpinnings, clinical objectives, and reported performance, which is essential for understanding the current state of the art and identifying future research directions.

Model Name	AI Architecture	Primary Application	Key Performance Metrics	Source(s)
CAPI-DETECT	Machine Learning (CatBoost)	Classification of SSc vs. non-SSc patterns; Staging of SSc patterns (early, active, late)	Accuracy: >90% (SSc vs. non-SSc); >92% (SSc staging) on full consensus data. Provides probability scores.	[59]
RESNET-34 PILOT	Deep Learning (CNN)	Classification of NVC images as normal vs. pathological; Capillary counting.	Sensitivity: 89.0%, Specificity: 86.9% (validation); Precision for capillary count: 96.48%.	[55]
MANCHESTER SYSTEM	Deep Learning (CNNs)	Subject-level probability of SSc from multi-finger images.	AUC: 97% (high-res images), 95% (low-cost USB scope); Outperforms expert consensus (Sens 82%, Spec 73%).	[64]
VISION TRANSFORMER (VIT)	Deep Learning (Transformer)	Identification of specific microangiopathic changes (e.g., giant capillaries, capillary loss).	AUC: 81.8–84.5% for various changes; AUC: 92.6% for giant capillaries. Performance comparable to human assessors.	[65]
ARTIX	Machine Learning	Objective quantification of Raynaud's phenomenon severity from mobile phone photos.	Successfully discriminated between RP patients and healthy controls during cold challenge ($p < 0.001$).	[62]

5. AI in Laboratory Diagnostics and Biomarkers

AI has introduced a wave of changes in laboratory medicine, enhancing the accuracy and efficiency of diagnostics [66]. It also facilitates the automation of analyses, interpretation of results, detection of anomalies, and acceleration of diagnostic procedures. These advancements enable the reduction of human error, improve operational efficiency, and enhance the quality of medical care. In clinical laboratories, automated operations increase reproducibility and the overall quality of work. Numerous applications of AI in laboratory medicine assist in the analysis of laboratory investigations; these applications can be applied to data derived from clinical chemical analyses as well as medical imaging [67].

Biomedical AI and laboratory medicine collectively form distinct fields within fundamental science and specialized engineering, often referred to as decision support systems, which are increasingly applied within laboratory diagnostics. Biomarker analysis based on AI facilitates personalized treatment plans and early detection of various disorders and diseases.

Both machine learning and deep learning equip laboratories with tools to handle large datasets, transforming predictive analysis into a practical reality. This revolutionizes the field of diagnostics and supports informed therapeutic decision-making. AI can complement, systematize, and analyze data obtained from medical investigations through automated systems that identify complex patterns and generate reliable results. Additionally, laboratory tests involving multiple elements can be automated through advanced processing techniques for multiple samples, micro-technologies, and methods compatible with automated workflows. Automated instruments can efficiently perform simple and well-defined measurement procedures—for example, pre-analytical blood sampling systems can provide well-prepared samples that meet the requirements of modern analytical technologies [68].

Machine learning, a branch of AI, holds the most significant practical application in laboratory medicine. It is used to predict test outcomes based on available data, thereby minimizing unnecessary testing.

Currently, various AI systems are employed daily in laboratory practices across the European Union and the United States (Table 2).

Table 2. Examples of commercial and research-based AI applications in laboratory medicine.

COMPANY/PROJECT	REGION	APPLICATION/DESCRIPTION
SIEMENS, GE, PHILIPS	EU and US	Automation and quality in laboratory diagnostics
EMPAIA	EU	Standardization and integration of AI in digital pathology
ABIONIC	EU/US	Rapid sepsis diagnosis via PSP
DXCOVER	EU/US	Liquid biopsy for early cancer detection
OWKIN	EU/US	Pre-screening and prognosis in oncology
SOPHIA GENETICS	Global	Genomic and multi-omics data analysis
APPLIED SPECTRAL IMAGING	US	Automated microscopy and analysis
DXPLAIN	US	Decision support based on symptoms and laboratory data
ML MODELS (CRP AND OTHERS)	EU (Slovenia), others	Differentiation between viral/bacterial infection using routine markers
CLINLABOMICS AND AI ANALYSIS	Global	AI across all phases of the laboratory process

5.1. Routine Tests

AI is frequently used in the analysis of Acute Phase Proteins (APP). CRP and ESR are non-specific markers, routinely tested when infections, autoimmune diseases, and other inflammatory processes are suspected. AI can be employed for automated interpretation, analyzing APP values in conjunction with other laboratory parameters (such as leukocytes, temperature, clinical history). Predictive models, involving algorithms that estimate the likelihood of bacterial infection or sepsis based on APP dynamics, can suggest when and whether to conduct further APP testing by integrating patient data from electronic health records, ultimately optimizing laboratory testing procedures. Combining age, sex, symptoms, and other laboratory data, AI can distinguish physiological increases from pathological ones, assessing the clinical significance of these indicators. In cases of deviations from normal, AI can signal the need for additional tests or consultations and detect potential anomalies. Over the long term, AI can monitor trends in ESR and CRP, linking these to specific diseases.

AI also finds applications in the detection of specific antibodies such as those against SARS-CoV-2 (COVID-19), autoantibodies (ANA, anti-DNA, etc.), tumor-associated antibodies (TAA), and antibodies against various infections (HBV, HCV, HIV). It assists with result classification, distinguishing false positives/negatives, especially at borderline values, and integrates these results within the clinical context. Complex algorithms analyze antibody presence relative to symptoms, epidemiological data, and vaccination status. AI models can also track immune responses over time, for example, following vaccination or infection, revealing how immune responses evolve. Machine learning models can analyze huge arrays of serological tests and help draw conclusions at the population level. It has applications in the diagnosis of infectious diseases, where AI can distinguish between acute and past infections by combining IgM/IgG data with the clinical picture, autoimmune diseases, where the detection of specific antibodies and the presence of specific symptoms make it easier to diagnose SLE, and in oncology, where tumor-associated antibodies (TAA) are studied. AI searches for immune signatures in certain types of cancer (e.g., ovarian or pancreatic cancer). The so-called "liquid biopsy" approach, in which AI recognizes patterns in the serum immune response associated with the early stages of cancer, is also impressive [69].

This application is expanding to complex disease subsets, such as Neuropsychiatric SLE (NPSLE), where early diagnosis is notoriously difficult due to subtle symptoms. Recent machine learning models have been developed to identify metabolic biomarkers from non-invasive neuroimaging data (proton magnetic resonance spectroscopy, or 1H-MRS), which can detect metabolic changes even when conventional MRI appears normal. By using AI to analyze this complex, often "noisy" spectroscopic data, researchers can identify metabolic signatures—such as changes in N-acetylaspartate (NAA)—that serve as potential biomarkers for early detection and for understanding the disease's progression [70].

Recognizing patterns in serological profiles using AI is a rapidly developing field that has enormous potential for improving the diagnosis, monitoring, and prediction of various diseases. This includes not only infectious diseases, but also autoimmune, oncological, and other conditions in which antibodies play a key role. A serological profile represents the data from tests for various antibodies in the blood (IgG, IgM, IgA, and those specific to viruses, bacteria, autoantigens, etc.). Recognizing patterns in serological profiles involves finding recurring structures or relationships between different antibodies, values, dynamics, and associated diseases. This is particularly useful when several tests are performed simultaneously (e.g., an autoantibody panel), data is monitored over time (e.g., dynamics in COVID-19, HIV, hepatitis, or when a patient has nonspecific symptoms and we are looking for an immunological "signature"). Machine learning and deep learning also have applications. Machine learning is used to classify results—e.g., "positive/negative/borderline" for a specific disease—as well as to group and identify patient groups with similar immune responses. It can also predict a diagnosis—e.g., the model predicts the probability of systemic lupus based on autoantibodies. In this way, a model trained on thousands of serological profiles can predict an autoimmune disease months before clinical symptoms appear.

Deep learning can detect complex, non-human-visible connections between different antibodies. It is used in multiplex serology—for example, tests with many parallel markers (20+ antibodies). It is particularly effective in time series—e.g., tracking the immune response after vaccination or infection. In this way, artificial intelligence expands the horizons of classical serology. From passive antibody measurement, it becomes a dynamic source of prognostic and diagnostic information when AI models recognize hidden patterns and relationships between antibodies, clinical picture, and future events.

5.2. Molecular Diagnostics

Numerous artificial intelligence models are used in genomics to detect and interpret genomic variants and biomarkers associated with diseases. Models such as DeepVariant (by Google) use convolutional neural networks to accurately detect genetic variants from next-generation sequencing (NGS) data, significantly reducing false positives [71]. DeepSEA helps interpret non-coding genes by predicting the functions of regulatory elements [72]. AI is also used to predict the structure and function of various proteins. The AlphaFold system has revolutionized the prediction of three-dimensional (3D) protein structures from amino acid sequences [73]. An initiative by UK Biobank and pharmaceutical companies is analyzing levels of up to 5400 proteins in a huge population, using AI to discover disease subtypes and new phenotype-genotype links.

Machine learning and deep learning are also applied in transcriptomics to discover diagnostic and prognostic signatures from RNA-Seq and other data, including diagnosis of acute myeloid leukemia, determination of subtypes in triple-negative breast cancer, prognosis in prostate or colorectal carcinoma [74]. Tools such as CIBERSORT, ESTIMATE, TIMER, and xCell use AI to analyze the immune environment and recognize immune cells and tumor microenvironments from transcriptomic data [75].

In proteomics, machine learning algorithms are used to discover protein biomarkers by identifying specific proteins as markers for early diagnosis, prognosis, and therapeutic response [10]. Studies such as this one on endometrial carcinoma combine explainable AI (XAI) with proteomics for prognosis using a small sample set [76]. The integration of genomics, proteomics, and metabolomics helps to classify patients into biological subtypes and prognostic groups [77].

5.3. Multi-Omics Integration

Integrated (Multi-Omics) diagnostics also has a wide range of applications. Multimodal deep learning models such as CNN, RNN, VAE, and GNN successfully integrate genomics, transcriptomics, and proteomics for tasks such as diagnosis, classification, and prediction [78]. AI is also applied in biomarker identification, discovering new biomarkers that are inaccessible to the traditional statistical approach by integrating multi-omic and clinical data. PandaOmics is a platform used to discover therapeutic targets and biomarkers from multi-omic data. It is also used in the development of risk assessment and subtyping models, particularly in the early classification of tumors, prognosis of survival, and therapeutic responses in different cancer types [79]. Explainable AI models (XAI) such as ARXAI increase trust and acceptance in clinical practice by visualizing why a particular marker or model has been selected [80]. An option for using images for biomarker prediction is also possible through Virchow2 and Pathomic Fusion, which integrates histological images with genomic data to improve prognosis and subtyping in glioma and renal cancer [81]. However, the practical application of these multi-omic models is significantly hindered by technical challenges, particularly the need for robust data harmonization, the management of batch effects arising from different proteomic and genomic platforms, and strategies for handling the high-dimensional data missingness that is typical of real-world, EHR-linked omics. Table 3 summarizes AI applications in genomics, transcriptomics, proteomics, and multi-omics integration relevant to rheumatology and precision medicine.

Table 3. Examples of AI use across omics layers in molecular diagnostics.

Field	Examples of AI Applications
Genomics	DeepVariant, DeepSEA, AlphaFold, biobank AI for proteomics and subtyping
Transcriptomics	Diagnosis and prognosis via RNA-Seq (AML, TNBC), immune microenvironment (CIBERSORT, etc.)
Proteomics	Discovery of prognostic protein markers, XAI models for early diagnosis
Multi-omics	Multimodal models (DL + ML), PandaOmics, integration of omics and clinical data
Explainability (xai)	Improving the reliability and interpretation of AI results
Images + data	Virchow2 (H & E slides to genomics), Pathomic Fusion (images + genomics)

Today, diagnostic systems are becoming cognitive partners to clinicians. Challenges arise from ethical and regulatory issues as well as limitations in interpreting contextual clinical features. Future opportunities that remain to be developed include more accurate diagnostics through AI combined with genetic data, as well as self-learning systems that improve their accuracy over time, which in practice will provide more personalized medicine through AI analysis of patient laboratory profiles.

6. AI-Assisted Clinical Decision Support Systems

Artificial Intelligence-Assisted Clinical Decision Support Systems (CDSS) are sophisticated computer programs designed to assist doctors in making complex decisions about patient care. In rheumatology these systems can analyze vast amounts of patient data—such as lab results, imaging scans, and clinical notes—to identify patterns that may be invisible to the human eye [3,82]. This helps rheumatologists to predict how a patient's disease might

progress, choose the most effective treatment from many options, and continuously monitor the patient's health, all with the goal of providing more personalized and effective care [83].

The primary areas of investigation within AI-assisted CDSS in rheumatology include disease activity prediction [84], treatment selection and monitoring [85], integration into electronic health records (EHR) [86].

6.1. Disease Activity Prediction

Disease activity prediction in rheumatology involves the use of computational models, primarily machine learning algorithms, to forecast future disease states based on baseline and longitudinal patient data [3,84]. These models analyze a wide range of variables, including clinical assessments, patient-reported outcomes, biomarkers, and imaging data, to predict outcomes such as the Disease Activity Score in 28 joints (DAS28) for rheumatoid arthritis (RA) or the likelihood of radiographic progression in axial spondyloarthritis (axSpA) [84,87].

Machine learning models, particularly regression models like Ridge and Lasso, have demonstrated strong performance in predicting 12-month disease activity in RA patients starting biologic therapies [84]. These models can predict continuous DAS28-CRP scores, offering a more nuanced forecast than simple binary remission/non-remission classifications.

In axSpA, machine learning algorithms such as the generalized linear model (GLM) and support vector machine (SVM) have shown promise in predicting radiographic progression over a two-year period. Key predictors identified by these models include baseline radiographic damage (mSASSS score) and the presence of syndesmophytes [87].

By identifying patients at high risk of disease progression or flare, these predictive models can enable clinicians to implement preemptive treatment strategies, potentially preventing irreversible joint damage and improving long-term outcomes [82].

6.2. Treatment Selection and Monitoring

AI-driven treatment selection and monitoring refer to the application of predictive analytics to personalize therapeutic interventions in rheumatology. These systems integrate multimodal data, including genomics, proteomics, and clinical information, to predict a patient's likely response to a specific drug, thereby moving away from a traditional "trial-and-error" approach towards precision medicine [85]. AI models have shown the potential to predict patient responses to specific medications, such as methotrexate in RA, by combining clinical characteristics with pharmacogenomic data. This allows for the identification of patients most likely to benefit from a particular treatment, improving efficacy and reducing the time to effective disease control [85].

Beyond initial treatment selection, AI can be used for continuous monitoring of treatment response, helping to identify patients who are not responding optimally and may require a change in therapy [83].

Generative AI and large language models (LLMs) are emerging as powerful tools that can function as clinical decision support systems, assisting with treatment optimization and providing up-to-date information to both clinicians and patients [1].

6.3. Integration into Electronic Health Records (EHR)

The integration of AI-assisted CDSS into EHRs involves embedding these tools directly into the clinical workflow, allowing for the automated extraction and analysis of patient data and the presentation of real-time, actionable insights to clinicians at the point of care [86]. This integration is crucial for translating the potential of AI into tangible improvements in patient outcomes. However, this step remains a major practical barrier, impeded by persistent EHR interoperability challenges and the slow adoption of modern data standards

like Fast Healthcare Interoperability Resources (FHIR), which are necessary for seamless data exchange between AI tools and clinical systems.

Natural Language Processing (NLP) is a key technology for EHR integration, as it enables the extraction of valuable information from unstructured clinical notes, which often contain crucial details about a patient's history, symptoms, and response to treatment [17,88]. By automating data extraction and analysis, AI-powered EHRs can reduce the administrative burden on clinicians, freeing up time for direct patient care [86]. Integrated CDSS can provide alerts and reminders to clinicians, for example, by identifying patients who are overdue for monitoring or who may be at high risk for disease flares, thus supporting proactive and preventative care [83].

7. Discussion: Challenges, Limitations, and Future Perspectives

Despite its promise, the path to clinical integration of AI is impeded by significant, interconnected challenges. These hurdles span technical issues, validation requirements, ethical imperatives, and barriers to adoption.

7.1. Technical and Methodological Barriers

A primary obstacle is the nature of healthcare data, which is often heterogeneous, incomplete, and stored in siloed systems lacking interoperability and standardization [83,89]. This is a major challenge for training robust AI models, which require vast amounts of high-quality data. Compounding this issue, the scarcity of large, publicly available, and representative datasets specifically curated for rheumatology hinders the independent benchmarking and rigorous external validation essential for developing generalizable models. Furthermore, the "black box" nature of many advanced models, where the decision-making process is opaque, creates a significant barrier to clinical adoption due to a lack of transparency and explainability [16]. Finally, deploying these computationally intensive models requires significant infrastructure that may not be available in all clinical settings [89].

7.2. The Imperative of Validation and Generalizability

A critical gap exists between promising research results and the evidence required for real-world clinical use. Most AI research is conducted in controlled settings using data from a single institution, which does not guarantee performance in routine practice [90]. There is an urgent need for robust, multicenter clinical trials to prospectively validate the safety and utility of AI tools in diverse patient populations [21]. The fact that no AI-based tools have received FDA approval for rheumatology highlights this validation gap [91]. A related issue is generalizability; a model trained on one population may not perform accurately on another due to variations in patient characteristics and practice patterns [82,92]. This is often compounded by a lack of methodological rigor and adherence to reporting guidelines in AI research [20].

7.3. Ethical Dilemmas and Patient Data Protection

The use of AI raises profound ethical questions. A primary concern is algorithmic bias, where models trained on data reflecting societal biases can learn and amplify them, potentially worsening healthcare disparities [16,93]. For example, many foundational imaging and genomic datasets in rheumatology are derived predominantly from cohorts of European ancestry, risking poorer model performance and misdiagnosis in underrepresented patient populations. Data privacy is also paramount, as AI development relies on large volumes of sensitive patient information, necessitating strict adherence to regulations like HIPAA and GDPR to prevent data breaches and maintain trust [21]. Finally, establishing accountability when an AI system contributes to an adverse outcome remains a complex,

unresolved issue, with responsibility blurred between developers, healthcare organizations, and clinicians [19].

7.4. Barriers to Adoption: Clinician Acceptance and Trust

Ultimately, AI tools might fail if not accepted by clinicians. A key barrier is a lack of training and familiarity with AI; a 2025 survey found 73% of rheumatologists had never used AI in practice [94]. This contributes to a lack of trust, especially in non-transparent "black box" models [22]. To succeed, tools must integrate seamlessly into clinical workflows without increasing administrative burden [95]. Both clinicians and patients also express valid concerns that AI could erode the human element of the patient-doctor relationship [22,93].

7.5. Defining Translational Pathways for Clinical Integration

To bridge the research-to-practice gap, the field could shift toward large-scale, pragmatic clinical trials that evaluate AI tools in routine workflows [92]. A proposed framework suggests a phased evaluation process analogous to that for pharmaceuticals, assessing discovery, efficacy, and post-deployment safety [96]. Successful implementation requires clearly identifying the clinical problem, establishing robust data infrastructure and governance (e.g., MLOps, which refers to the operational management of production-level AI models to ensure performance and safety over time), and designing tools for seamless workflow integration [97].

7.6. The Crucial Role of Interdisciplinary Collaboration

Successful AI implementation requires deep, sustained interdisciplinary collaboration [92]. Integrated teams could include clinicians for domain expertise, data scientists for algorithm development, ethicists for navigating bias and privacy, administrators for workflow integration, and patients for the end-user perspective [96]. This "human-in-the-loop" approach is fundamental to building trustworthy and effective AI solutions [93].

7.7. Reforming Medical Education: Training AI-Fluent Rheumatologists

A significant knowledge gap exists among clinicians. To address this, AI education could be integrated into medical school and rheumatology fellowship curricula [98]. There is a clear demand for this, with the majority of US rheumatology fellows expressing interest in dedicated AI training [99]. This sentiment was echoed in a survey presented at the EULAR 2024 Congress, which found that 84% of participating European rheumatologists would appreciate dedicated AI training, leading to the conclusion that such training is 'needed'. These calls are beginning to be met by initiatives such as EULAR's 2024 educational webinars on machine learning and AI [100,101]. The goal is to cultivate "AI-fluent" rheumatologists who can critically appraise AI research, understand model limitations, and participate as informed collaborators in developing new technologies [17].

7.8. The Future Horizon: AI-Augmented Rheumatology

The future of rheumatology will be characterized by a synergy of human expertise and AI. This includes both discriminative AI for prediction and generative AI for knowledge synthesis and clinical decision support [1]. Hopefully, this convergence will advance precision medicine by synthesizing multimodal data—from EHRs and genomics to wearable sensors—to create dynamic, predictive models of disease for each patient [82]. This would enable a shift from static diagnosis to personalized forecasting of disease activity and treatment response. AI-driven "digital twins" (i.e., dynamic, virtual representations of a patient's physiology built from multimodal data) could revolutionize clinical trials, while continuous monitoring via wearables will support a proactive, truly personalized approach to managing chronic rheumatic diseases [1,82].

7.9. Limitations of the Review

This review, while structured, has several limitations. First, as a narrative review, it is susceptible to selection bias, despite our systematic search strategy. We aimed to synthesize a broad, interdisciplinary field rather than conduct a formal systematic review or meta-analysis, and thus may have omitted relevant studies.

Second, the field of AI in rheumatology is evolving at an exceptional pace. While our search included recent publications up to mid-2025, new preprints and clinical trial data are published continuously, meaning some emerging tools or validation studies may not be captured. The inclusion of preprints was intended to mitigate this, but these sources have not completed formal peer review. Furthermore, our review was restricted to English-language articles, potentially excluding valuable research from non-Anglophone countries.

Finally, the primary literature itself presents significant, recurring limitations that were consistently encountered during our analysis. These include a predominance of single-center studies with small, homogenous cohorts, a scarcity of prospective, external validation in diverse, real-world clinical settings, and a lack of large, public, and representative datasets for benchmarking. We also noted significant gaps in the literature regarding data harmonization challenges (e.g., batch effects), algorithmic bias from unrepresentative training data, and the scalability of tools across different hardware (e.g., low-cost vs. high-end devices). These limitations in the available evidence necessarily constrain the conclusions that can be drawn about the clinical readiness of many promising AI tools.

8. Conclusions

Artificial intelligence is moving from concept to clinic in rheumatology, with the strongest near-term utility in imaging and laboratory workflows that strain human time and consistency. In imaging, ML/DL tools can standardize MSUS synovitis scoring, flag inflammatory and structural MRI features (e.g., BME, erosions), assist DECT/HRCT interpretation for gout and CTD-ILD, and accelerate radiographic progression scoring—reducing inter-observer variability while preserving expert oversight. Capillaroscopy is an early beneficiary: automated detection and quantification of giant capillaries, density, and hemorrhages can turn a subjective, slow test into an objective point-of-care aid. In the lab, AI can triage routine markers (CRP/ESR), de-noise serology (borderline results, false positives), and fuse multi-omics with clinical data to provide earlier, more individualized risk signals. These capabilities enable AI-assisted CDSS to predict disease activity, personalize treatment selection/monitoring, and deliver timely, in-workflow prompts via the EHR. Yet broad adoption hinges on rigorous external validation in diverse populations, attention to explainability, and robust data governance aligned with GDPR/HIPAA. Clinicians should expect "augmented" rather than autonomous AI: tools that pre-score, pre-segment, or pre-rank, with the final call remaining clinical. Practical first steps include piloting AI on well-defined use cases (e.g., automated MSUS grading or ILD quantification), measuring impact on time, agreement, and patient outcomes, and building local MLOps processes for monitoring drift and safety. Training the workforce is essential—short, case-based modules on reading model outputs, failure modes, and bias mitigation will build trust and competence. Ethically, teams must track performance by subgroup, document human-in-the-loop checkpoints, and communicate uncertainties to patients. If implemented this way, AI will help rheumatology shift from episodic diagnosis to proactive, precision care—using integrated signals from images, labs, and wearables to anticipate flares, tailor therapy, and improve outcomes.

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