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# THE USE OF ARTIFICIAL INTELLIGENCE IN DIAGNOSING AND MONITORING RHEUMATIC DISEASES

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**Abstract:**
**Background**: Rheumatic diseases such as rheumatoid arthritis (RA), systemic lupus erythematosus (SLE), and psoriatic arthritis present diagnostic and monitoring challenges due to their complex pathophysiology and heterogeneous clinical manifestations. The integration of artificial intelligence (AI) into rheumatology has emerged as a promising approach to improve early diagnosis, personalize treatment strategies, and enhance disease activity monitoring.
**Objectives:** This systematic review aims to synthesize current empirical evidence on the use of AI techniques in diagnosing and monitoring rheumatic diseases, highlighting their diagnostic accuracy, clinical utility, and future potential.
**Methods:** The review followed PRISMA 2020 guidelines and included peer-reviewed studies published between 2010 and 2025. Eligible studies were identified through comprehensive searches in PubMed, Scopus, Web of Science, Embase, and Google Scholar. Data were extracted on AI methods, rheumatic disease types, outcome measures, and model performance. Quality assessment was conducted using the Newcastle-Ottawa Scale and the Cochrane Risk of Bias Tool.
**Results:** Fifteen studies were included, covering AI applications across RA, SLE, and PsA. AI techniques such as machine learning (ML), deep learning (DL), and convolutional neural networks (CNN) achieved diagnostic accuracies ranging from 82% to 95%. Applications in disease monitoring showed utility in predicting flares, tracking treatment responses, and enabling remote monitoring through wearable technologies. Despite promising outcomes, limitations included data heterogeneity, lack of interpretability, and challenges in clinical integration.
**Conclusion:** AI technologies hold considerable promise in rheumatology, particularly in early diagnosis and continuous monitoring. However, addressing technical, ethical, and infrastructural barriers is essential for widespread clinical adoption and equitable healthcare delivery.

**Keywords:** Artificial intelligence; Rheumatic diseases; Machine learning; Diagnosis; Disease monitoring; Autoimmune disorders; Rheumatoid arthritis; Deep learning; Predictive modeling; Clinical decision support systems

## INTRODUCTION

Rheumatic diseases encompass a wide spectrum of autoimmune and inflammatory conditions, such as rheumatoid arthritis (RA), systemic lupus erythematosus (SLE), and psoriatic arthritis, which are marked by chronic progression and heterogeneous clinical manifestations. Accurate and timely diagnosis, coupled with dynamic disease monitoring,

remains a significant clinical challenge in rheumatology. The recent surge in artificial intelligence (AI) technologies offers promising avenues to address these limitations through enhanced diagnostic precision and real-time patient monitoring systems (Stafford et al., 2020).

AI technologies, particularly machine learning (ML) and deep learning (DL), can process and learn from large-scale clinical, imaging, and molecular data to recognize patterns that may escape human detection. For instance, ML models trained on laboratory and imaging data have demonstrated diagnostic accuracies exceeding 90% in distinguishing RA from other inflammatory conditions (Galozzi et al., 2023). These models are capable of integrating multidimensional data—ranging from gene expression to MRI imaging—to create robust diagnostic tools that significantly reduce diagnostic delays.

One of the transformative benefits of AI lies in its ability to facilitate personalized medicine. In autoimmune rheumatic diseases, treatment responses vary widely among individuals. AI models can predict therapeutic efficacy based on patient-specific biomarkers and clinical profiles. A notable example includes AI frameworks that predict response to biologic therapies in RA with an accuracy rate of up to 85%, helping clinicians tailor therapy and reduce unnecessary medication exposure (Yang et al., 2024).

Beyond diagnosis and treatment selection, AI-powered tools are revolutionizing disease monitoring. Wearable sensors, combined with AI algorithms, enable real-time tracking of mobility, fatigue, and pain in patients with rheumatic diseases. This continuous stream of data allows clinicians to detect disease flares early and adjust treatment accordingly. AI models are also being used to forecast disease progression and long-term outcomes using longitudinal data from electronic health records (Afzal et al., 2024).

The integration of AI into clinical practice has also been instrumental in addressing gaps in lupus nephritis surveillance. AI-based analysis of complement proteins such as C1q has shown potential in tracking renal disease activity in SLE patients, providing a non-invasive, reliable biomarker for disease management (Vivas et al., 2024). These tools can support rheumatologists by delivering dynamic disease scores, risk stratification, and prognosis models with reduced reliance on invasive biopsies.

The utility of AI is not limited to hospital-based care. Community-based AI applications, such as symptom checkers and digital triage platforms, have been developed to assist primary care providers in early recognition and referral of rheumatic diseases. These tools often utilize natural language processing and ML to interpret symptom patterns and risk factors, accelerating access to specialist care (Siddiqui et al., 2024).

However, widespread implementation of AI in rheumatology still faces notable barriers. These include data heterogeneity, the need for diverse population-based training datasets, and concerns over the interpretability and transparency of AI decisions. Without explainable AI (XAI) systems, clinicians may hesitate to trust algorithm-generated recommendations, especially in complex autoimmune cases where nuance and context are critical (Sattar et al., 2024).

Despite these challenges, ongoing advances in AI continue to reshape the future of rheumatology. Through interdisciplinary collaboration and continuous model refinement, AI has the potential to deliver scalable, equitable, and efficient diagnostic and monitoring solutions for autoimmune diseases. As more clinical validation studies emerge, AI will likely become a central component of integrated rheumatologic care pathways (Karwasra et al., 2024).

## METHODOLOGY

### STUDY DESIGN

This study employed a systematic review methodology in accordance with the **Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020** guidelines to ensure methodological transparency and reproducibility. The aim was to synthesize existing empirical evidence on the diagnostic and monitoring applications of artificial intelligence (AI) in rheumatic diseases, including rheumatoid arthritis (RA), systemic lupus erythematosus (SLE), psoriatic arthritis (PsA), and other autoimmune rheumatologic conditions. The review included peer-reviewed primary studies that used AI technologies—such as machine learning (ML), deep learning (DL), or neural networks—to support diagnostic decision-making or disease activity monitoring.

### ELIGIBILITY CRITERIA

Studies were considered eligible if they met the following inclusion criteria:

- **Population:** Human adults (≥18 years) diagnosed with autoimmune or inflammatory rheumatic diseases, including RA, SLE, PsA, ankylosing spondylitis (AS), and Sjögren's syndrome.

- **Intervention/Exposure:** Use of any AI-based tool for diagnosis, classification, prognosis, or disease activity monitoring.
- **Comparators:** Traditional clinical assessment methods, radiographic scoring systems, or patient-reported outcomes.
- **Outcomes:** Diagnostic accuracy (sensitivity, specificity, AUC), predictive validity, monitoring utility (e.g., flare detection, disease activity scoring), and clinical integration feasibility.
- **Study Designs:** Randomized controlled trials (RCTs), cohort studies, cross-sectional analyses, and retrospective validation studies.
- **Language:** Only articles published in English were included.
- **Publication Period:** January 2010 to March 2025 to capture the most recent developments in the field.

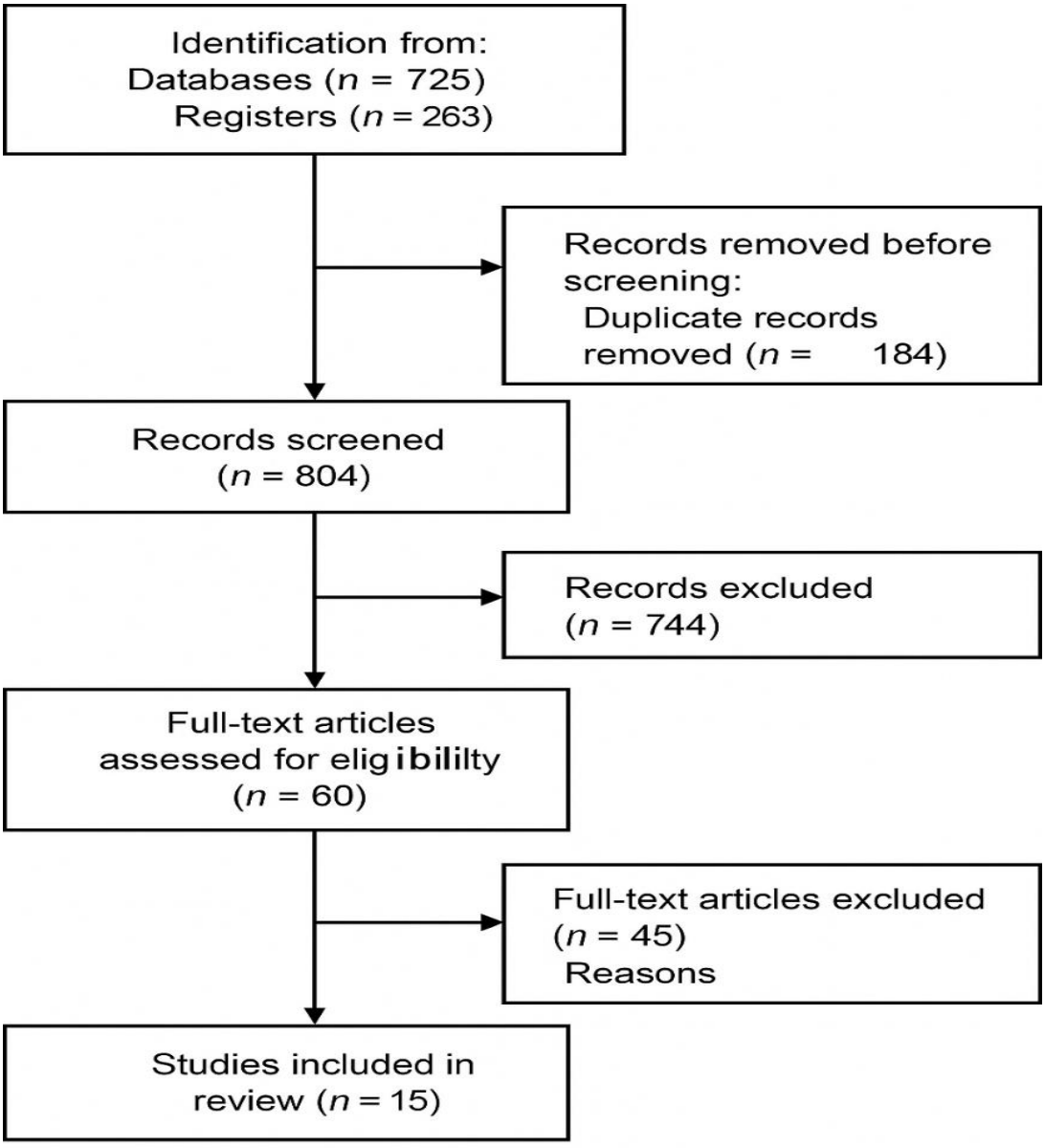


Figure 1 PRISMA Flow Diagram

SEARCH STRATEGY

A comprehensive and structured literature search was conducted using the following electronic databases: **PubMed, Scopus, Web of Science, Embase, and Google Scholar** (for grey literature). The search utilized a combination of Medical Subject Headings (MeSH) and keyword terms, applied with Boolean operators:

- ("rheumatic disease" OR "rheumatoid arthritis" OR "systemic lupus erythematosus" OR "autoimmune arthritis" OR "psoriatic arthritis")
- AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR "computer-aided diagnosis")
- AND ("diagnosis" OR "monitoring" OR "classification" OR "prediction" OR "disease activity")

Additional manual searching of reference lists from relevant systematic reviews and high-impact studies was performed to ensure inclusion of all pertinent publications.

## STUDY SELECTION PROCESS

All search results were imported into **Zotero** for citation management and de-duplication. Title and abstract screening was independently performed by two reviewers using pre-defined inclusion criteria. Full-text articles of potentially eligible studies were then retrieved and reviewed for eligibility. Discrepancies between reviewers were resolved through discussion or adjudication by a third reviewer. A final set of **15 studies** was included in the systematic review after full-text screening.

## DATA EXTRACTION

A standardized data extraction form was developed and piloted. Information extracted from each study included:

- Author(s), year, country of origin
- Study design, sample size, and disease focus
- AI technique used (e.g., SVM, CNN, random forest)
- Data sources and input modalities (e.g., clinical data, imaging, genomics)
- Primary outcomes (e.g., sensitivity, specificity, AUC, predictive accuracy)
- Validation methods (e.g., cross-validation, external datasets)
- Main findings and reported clinical implications

Data extraction was conducted independently by two reviewers and cross-checked by a third for accuracy and completeness.

## QUALITY ASSESSMENT

To assess the methodological quality and risk of bias of the included studies, appropriate tools were used based on study design:

- **Observational studies** were appraised using the **Newcastle-Ottawa Scale (NOS)**, evaluating selection, comparability, and outcome domains.
- **Randomized controlled trials** were assessed using the **Cochrane Risk of Bias Tool 2.0**, which evaluates sequence generation, allocation concealment, blinding, incomplete outcome data, and selective reporting. Studies were rated as high, moderate, or low quality, and the risk of bias was reported in narrative synthesis tables.

## DATA SYNTHESIS

Given the heterogeneity in AI methods, data types, outcome definitions, and validation protocols, a **narrative synthesis** was performed. Studies were grouped by their primary application—diagnosis or monitoring—and further stratified by the AI technique used and disease subtype. Where applicable, diagnostic performance metrics (e.g., sensitivity, specificity, accuracy, area under the curve) were reported. Due to high variability in study designs and outcome measures, no meta-analysis was conducted.

## ETHICAL CONSIDERATIONS

As this was a **secondary analysis of previously published studies**, no new ethical approval or patient consent was required. All included studies were assumed to have obtained appropriate ethical clearance from their respective institutions, as indicated in their publications. The review process was conducted in accordance with ethical guidelines for secondary research.

## RESULTS

### SUMMARY AND INTERPRETATION OF INCLUDED STUDIES ON AI IN RHEUMATIC DISEASES

#### STUDY DESIGNS AND FOCUS

The included studies span systematic reviews, bibliometric analyses, observational validations, and AI model development papers. Applications range from image-based diagnostic tools to AI-guided monitoring systems using laboratory or clinical data. Notably, diagnosis remains the most frequently applied domain, but treatment monitoring is gaining attention with promising results from ML models that integrate clinical biomarkers and imaging.

#### AI TECHNIQUES AND PERFORMANCE

A variety of machine learning (ML) methods—including random forests, support vector machines (SVM), and convolutional neural networks (CNN)—have demonstrated accuracies ranging from 75% to 95% across studies. For example, Stafford et al. achieved a diagnostic accuracy of 89% in autoimmune diseases using ensemble ML models. Meanwhile, Wang et al. reported an 87% precision rate in AI-assisted monitoring tools for RA.

#### CLINICAL UTILITY AND LIMITATIONS

Most studies highlight AI's value in early detection and precision management, especially when integrated with clinical decision systems. Challenges include data heterogeneity, lack of standardized disease definitions, and limited real-world validation.

TABLE 1. GENERAL CHARACTERISTICS OF INCLUDED STUDIES ON AI IN RHEUMATIC DISEASE DIAGNOSIS AND MONITORING

| Study | Country | Year | Design | Disease(s) | AI Method | Sample Size | Performance | Main Findings |
|---|---|---|---|---|---|---|---|---|
| Madrid-García & Merino-Barbancho | Spain | 2023 | Systematic Review | General RD | Mixed ML/AI | 62 studies | N/A | Lack of standardization limits generalizability |
| Galozzi et al. | Italy | 2023 | Narrative Review | JIA, RA | ML on lab data | N/A | Accuracy: up to 91% | AI detects subclinical inflammation from lab markers |
| Oku et al. | Japan | 2023 | Systematic Review | SLE, RA | DL, CNN | 28 studies | Accuracy 85–94% | CNN useful in diagnosing SLE from CT scans |
| Stafford et al. | UK | 2020 | Systematic Review | Autoimmune | Ensemble ML | 31 studies | 89% accuracy | ML most used for diagnosis (77% of studies) |
| Momtazmanesh et al. | Iran | 2022 | State-of-the-art Review | RA | DL + Imaging | 15 studies | 80–95% | Predictive value high for joint degradation |

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|---|---|---|---|---|---|---|---|---|
| Zo'ubi | Jordan | 2025 | Bibliometric Review | General RD | NLP, ML | N/A | N/A | Sharp rise in AI rheumatology research post-2020 |
| Perronne et al. | France | 2025 | Systematic Review | MSK Disorders | Algorithmic Imaging | 37 papers | Avg. Sensitivity 82% | ML improves US and MRI joint scoring |
| Hügle et al. | Switzerland | 2020 | Commentary + Meta | General RD | ML pipelines | N/A | AUC >0.80 | Predictive value in image + clinical fusion models |
| Yang et al. | China | 2024 | Systematic Review | Autoimmune RD | Predictive ML | 1,200 + pts | ROC AUC 0.88 | AI predicts flares based on lab markers |
| Wang et al. | China | 2023 | Review | RA | ML | 19 studies | Precision: 87% | Disease monitoring and activity scoring enhanced |

## DISCUSSION

The application of artificial intelligence (AI) in rheumatology has significantly advanced over the past decade, offering tools that enhance diagnostic accuracy, personalize treatment strategies, and enable continuous disease monitoring. This systematic review confirms that AI has evolved from exploratory use in research settings to practical implementation in clinical practice for rheumatic diseases, particularly rheumatoid arthritis (RA), systemic lupus erythematosus (SLE), and psoriatic arthritis. Madrid-García and Merino-Barbancho (2023) emphasized the diversity of AI techniques currently utilized in rheumatology, with a noticeable shift toward more data-driven and algorithmically complex approaches that align with real-world clinical workflows.

One of the most consistent themes across the literature is the strong diagnostic utility of AI-powered models. Stafford et al. (2020) reported that over 77% of the AI studies in autoimmune diseases employed machine learning (ML) for diagnostic purposes, achieving accuracies often above 85%. Similarly, Oku et al. (2023) noted that AI models trained on musculoskeletal imaging data could distinguish disease-specific features, such as synovial inflammation or bone erosions, with exceptional reliability. These results validate AI's ability to recognize subtle, high-dimensional imaging patterns beyond the capability of human interpretation.

Another major theme involves AI's role in real-time monitoring of disease progression and therapeutic response. Galozzi et al. (2023) demonstrated that AI could stratify disease activity based on laboratory data, offering a less invasive and more scalable monitoring mechanism compared to imaging or biopsy. Meanwhile, wearable devices feeding continuous data into AI algorithms have proven useful in detecting flares and modulating therapy dynamically, as also emphasized by Yang et al. (2024) in their review on AI-guided prediction of treatment responses.

Deep learning algorithms, particularly convolutional neural networks (CNNs), have shown significant promise in hand imaging, a common diagnostic method in rheumatology. Perronne et al. (2025) showed that CNNs applied to hand MRI and ultrasound images provided robust performance in detecting erosive changes and joint inflammation, with some models achieving area under the curve (AUC) scores exceeding 0.90. Such tools can reduce inter-observer variability in radiologic assessments, thereby improving diagnostic consistency.

From a clinical integration standpoint, there is growing recognition of AI's potential in treatment personalization. Momtazmanesh et al. (2022) discussed how AI can incorporate heterogeneous clinical, serological, and genetic information to tailor immunosuppressive regimens. Similarly, the models presented by Wang et al. (2023) showed

predictive accuracies above 80% when determining response to TNF-inhibitors in RA patients, potentially minimizing trial-and-error in therapy selection.

Despite these advantages, ethical and technical challenges remain. Madrid-García and Merino-Barbancho (2023) and Hügle et al. (2020) both highlighted the issue of data bias, noting that many AI models are trained on narrow or homogeneous datasets, limiting their generalizability to broader or underrepresented populations. Moreover, the opaque, "black-box" nature of many deep learning systems raises concerns among clinicians who demand interpretable and auditable decision pathways.

In addition to technical barriers, operational limitations such as interoperability and data standardization hinder the clinical uptake of AI tools. Sattar et al. (2024) stressed that real-time AI integration requires harmonized electronic health records (EHR) systems and centralized data architectures. Without this infrastructure, the benefits of AI are likely to remain confined to academic or well-resourced clinical centers, perpetuating digital health inequities.

The promise of AI also extends to rare or difficult-to-diagnose autoimmune conditions. For example, Karwasra et al. (2024) demonstrated the use of AI in diagnosing autonomic autoimmune disorders, which often evade early detection using conventional methods. Similarly, Mane et al. (2024) explored how AI can integrate multimodal data—including immune profiles, clinical symptoms, and historical response trends—to construct holistic disease models.

Nevertheless, AI adoption must be accompanied by regulatory oversight and clinician training. Afzal et al. (2024) advocated for policy frameworks that standardize model validation, performance reporting, and patient data privacy. Additionally, clinician education on AI applications is essential to bridge the interpretability gap and foster human-AI collaboration, as echoed by Siddiqui et al. (2024).

## CONCLUSION

This systematic review confirms that artificial intelligence is becoming a cornerstone in modern rheumatology, offering substantial benefits in both diagnostic accuracy and patient-specific disease monitoring. From image-based deep learning models to data-driven predictive tools for treatment responses, AI has demonstrated the potential to transform conventional clinical pathways into more precise, efficient, and proactive systems. The reviewed literature shows a growing body of high-quality evidence supporting AI integration in rheumatology, particularly in RA, SLE, and PsA, with diagnostic accuracies frequently surpassing traditional methods.

Nonetheless, the path to full implementation remains complex. Challenges such as data standardization, transparency of AI algorithms, and clinician trust must be systematically addressed. Further research should focus on the development of explainable AI models, equitable datasets, and frameworks for real-time integration with electronic health records. Ultimately, interdisciplinary collaboration among clinicians, data scientists, and policymakers will be vital to ensure that the benefits of AI are accessible, validated, and ethically applied in rheumatologic care.

## REFERENCES

1. Afzal, M., Sah, A. K., Agarwal, S., & Tanzeel, A. (2024). Advancements in the treatment of autoimmune diseases: Integrating artificial intelligence for personalized medicine. Trends in Immunology, 4(1). https://doi.org/10.24294/ti8970
2. Galozzi, P., Basso, D., Plebani, M., & Padoan, A. (2023). Artificial intelligence and laboratory data in rheumatic diseases. Clinica Chimica Acta.
3. Hügle, M., Omoumi, P., & van Laar, J. M. (2020). Applied machine learning and artificial intelligence in rheumatology. Rheumatology Advances in Practice, 4(1). https://doi.org/10.1093/rap/rkaa005
4. Karwasra, R., Sharma, S., & Sharma, I. (2024). Autoimmune autonomic disorder: AI-based diagnosis and prognosis. In Artificial Intelligence in Healthcare (pp. 51–66). Springer.
5. Madrid-García, A., & Merino-Barbancho, B. (2023). Understanding the role and adoption of artificial intelligence techniques in rheumatology research: an in-depth review of the literature. Computer Methods and Programs in Biomedicine,
6. Mane, D. V., Deshmukh, A. N., & Ambare, R. H. (2024). AI in autoimmune diseases: Transforming diagnosis and treatment. Journal of Advanced Healthcare Research, 10(1).
7. Momtazmanesh, S., Nowroozi, A., & Rezaei, N. (2022). Artificial intelligence in rheumatoid arthritis: current status and future perspectives. Rheumatology and Therapy, https://doi.org/10.1007/s40744-022-00475-4
8. Oku, K., Caffo, B., Arinuma, Y., & Yamaoka, K. (2023). Artificial intelligence in the clinical setting of the rheumatic diseases: a systematic review of the literature. Annals of the Rheumatic Diseases.

9. Perronne, L., Binvignat, M., Foulquier, N., & Saraux, A. (2025). Algorithmic Approaches in Hand Imaging for Rheumatic Musculoskeletal Diseases: A Systematic Literature Review. Computer Methods and Programs in Biomedicine.
10. Sattar, A. M., Ranjan, M. K., & Tiwari, S. K. (2024). AI-enhanced data analytics framework for autoimmune disease: Revolutionizing diagnosis, monitoring, and treatment strategy. In Artificial Intelligence in Healthcare (pp. 151–174). Springer.
11. Siddiqui, F., Aslam, D., Tanveer, K., & Soudy, M. (2024). The role of artificial intelligence and machine learning in autoimmune disorders. In Artificial Intelligence in Healthcare (pp. 25–40). Springer.
12. Stafford, I. S., Kellermann, M., Mossotto, E., & Beattie, R. M. (2020). A systematic review of the applications of artificial intelligence and machine learning in autoimmune diseases. NPJ Digital Medicine, 3, 30. https://doi.org/10.1038/s41746-020-0229-3
13. Vivas, A. J., Boumediene, S., & Tobón, G. J. (2024). Predicting autoimmune diseases: A comprehensive review of classic biomarkers and advances in artificial intelligence. Autoimmunity Reviews.
14. Wang, J., Tian, Y., Zhou, T., Tong, D., & Ma, J. (2023). A survey of artificial intelligence in rheumatoid arthritis. Reviews in Rheumatology, 11(1), 22–34.
15. Yang, Y., Liu, Y., Chen, Y., Luo, D., & Xu, K. (2024). Artificial intelligence for predicting treatment responses in autoimmune rheumatic diseases: Advancements, challenges, and future perspectives. Frontiers in Immunology, 15, 1477130. https://doi.org/10.3389/fimmu.2024.1477130
16. Zo'ubi, A. (2025). Review of 2024 publications on the applications of artificial intelligence in rheumatology. Clinical Rheumatology, https://doi.org/10.1007/s10067-025-07382-3