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editorial-office@sciformat.ca

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ARTIFICIAL INTELLIGENCE IN REMOTE MONITORING OF RHEUMATOID ARTHRITIS: DIGITAL BIOMARKERS, PATIENT ENGAGEMENT, AND BARRIERS TO IMPLEMENTATION

Martyna Szymczyk *(Corresponding Author, Email: wiktorwawrzyniec29@gmail.com)*
Jan Kochanowski University, Kielce, Świętokrzyskie, Poland
ORCID ID: 0009-0005-0772-7119

Jagoda Pałubska
Independent Public Health Care Institution of the Ministry of the Interior and Administration in Kielce named after St. John Paul II, Kielce, Poland
ORCID ID: 0009-0000-3833-7977

Oliwer Muller
Kielce Hospital of St. Aleksandra Sp. z o.o., Kielce, Poland
ORCID ID: 0009-0005-6197-8461

Anna Szot
Jan Kochanowski University, Kielce, Świętokrzyskie, Poland
ORCID ID: 0009-0003-2613-1068

Dominik Szydełko
Wojewódzki Szpital Zespolony, Kielce, Świętokrzyskie, Poland
ORCID ID: 0009-0002-9907-858X

Katarzyna Rosa
Uniwersyteckie Centrum Kliniczne, Gdańsk, Pomerania, Poland
ORCID ID: 0009-0005-9307-4774

Agata Słoma
Uniwersyteckie Centrum Kliniczne, Gdańsk, Pomerania, Poland
ORCID ID: 0009-0004-6807-7706

Daria Danielczyk
Wojewódzki Szpital Zespolony, Kielce, Świętokrzyskie, Poland
ORCID ID: 0009-0002-4955-4883

Wiktor Czyżewski
Independent Public Health Care Institution of the Ministry of the Interior and Administration in Kielce named after St. John Paul II, Kielce, Poland
ORCID ID: 0009-0003-0277-8203

Natalia Malatyńska
Jan Kochanowski University, Kielce, Świętokrzyskie, Poland
ORCID ID: 0009-0005-3824-8225

ABSTRACT

The growing availability of patient-generated health data is reshaping how rheumatoid arthritis (RA) can be monitored beyond the clinic. This narrative review examines how artificial intelligence (AI) supports remote RA monitoring through digital biomarkers, patient-reported tools, and connected technologies, with particular attention to patient engagement and implementation barriers. A structured PubMed-based search identified literature on RA, AI, machine learning, remote monitoring, wearables, smartphone applications, telemedicine, and digital health. Across the reviewed studies, AI was used mainly to interpret longitudinal patient-reported outcomes, activity-tracker data, and daily smartphone symptom reports. Collectively, these approaches suggest that remote monitoring can enrich between-visit assessment, support flare detection, and provide a more continuous picture of disease experience than episodic clinic review alone. Yet the evidence base remains uneven, with many studies limited by small samples, short follow-up, exploratory modeling, and heterogeneous outcomes. The literature also makes clear that the practical success of remote monitoring depends on more than algorithmic performance; usability, adherence, digital literacy, trust, privacy, workflow integration, and equitable access all shape whether these tools can function in routine care. The most credible near-term model is therefore not fully automated monitoring, but hybrid, clinician-linked systems co-designed with users. AI-supported remote monitoring is a promising extension of RA care, but its long-term value will depend on whether it can be validated rigorously and implemented in ways that are patient-centered, clinically meaningful, and socially inclusive.

KEYWORDS

Rheumatoid Arthritis, Artificial Intelligence, Remote Monitoring, Digital Biomarkers, Patient Engagement, Telemedicine

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1. Introduction

Rheumatoid arthritis (RA) is monitored in the clinic but lived in the intervals between visits. Pain, stiffness, fatigue, and loss of function do not emerge according to appointment schedules, and clinically important worsening may unfold days or weeks before it is formally documented. This temporal mismatch sits uneasily with treat-to-target care, which assumes that disease activity can be recognized early enough to support timely adjustment of therapy. In routine practice, however, follow-up still depends heavily on episodic consultations and clinician-derived indices that offer structured yet infrequent snapshots of a much more dynamic disease course. Recent reviews of artificial intelligence and mobile health in RA have therefore framed digital monitoring not as a technological embellishment, but as a response to a real clinical, organizational, and experiential gap (Momtazmanesh et al., 2022; Seppen et al., 2020).

The importance of this gap extends beyond measurement itself. Visit-bound assessment can leave meaningful symptom escalation invisible to the clinical team, while repeated in-person monitoring may be burdensome for patients and difficult to sustain in overstretched health systems. Travel, time away from work, workforce shortages, and growing demand all shape whether conventional follow-up is feasible at the intensity that modern care models require. Remote monitoring has consequently gained attention not only because it promises better data, but also because it aligns with broader efforts to make chronic care more flexible, responsive, and realistic in everyday life (Seppen et al., 2020; Sloan et al., 2022).

Digital health technologies offer a route toward that model by allowing symptoms, behaviors, and health routines to be observed beyond the clinic. In RA, this ecosystem now includes electronic patient-reported outcomes, smartphone apps, asynchronous messaging pathways, consumer wearables, telemonitoring platforms, and clinician-facing dashboards that visualize longitudinal change. Importantly, remote monitoring should not be reduced to telemedicine alone. A video or telephone appointment may reproduce a conventional consultation at a distance, whereas monitoring technologies generate repeated signals in between consultations and may support follow-up that is continuous rather than episodic. Their distinctive contribution lies in the creation of patient-generated data streams that can potentially be linked to disease control, flare dynamics, and service need (Seppen et al., 2020; Sloan et al., 2022).

Artificial intelligence becomes especially relevant once monitoring moves outside the clinic, because longitudinal digital data are abundant yet not inherently interpretable. A handful of questionnaire scores can be reviewed by a clinician with ease, but months of repeated symptom reports, step counts, wearable-derived behaviors, and text-based updates are harder to translate into timely decisions without computational support. Machine learning approaches offer a way to recognize patterns within these streams, estimate disease state, and flag changes that may warrant attention. In the current RA literature, the most persuasive use cases involve the classification of physician-derived disease activity from repeated patient-reported outcomes, the analysis of passive activity-tracker data, and the detection of symptom patterns that precede self-reported flares (Curtis et al., 2022; Gandrup et al., 2024; Rao et al., 2023).

The significance of these developments is not purely technical. The value of remote monitoring depends just as much on what is measured, who is willing and able to contribute data, how those data are interpreted, and whether the resulting outputs fit routine care. Qualitative work has shown that patients prioritize symptom fluctuation, pain, fatigue, mobility, triggers, and the day-to-day impact of disease when asked what should be monitored remotely, suggesting that user-relevant measurement may differ from what is easiest to collect in conventional clinic pathways (White et al., 2021). Survey research in rheumatology also indicates that enthusiasm for digital tools does not automatically translate into sustained use. Awareness of trustworthy tools, confidence in data security, ease of use, and digital literacy all shape whether technology becomes part of routine self-management or remains an unused promise (Knitza et al., 2020).

These issues become even more salient when remote monitoring is viewed through a technology-and-society lens. Innovation may expand access and flexibility, yet it may also reproduce existing inequities if devices, connectivity, digital confidence, or trust in remote care are unevenly distributed. Studies in inflammatory rheumatic diseases suggest that some patients, especially those who are older, digitally excluded, or less confident online, may be less able to benefit from technology-enabled pathways. Moreover, even when remote care is valued for convenience, patients and clinicians may still judge it to be less accurate or less relational than face-to-face assessment (Hider et al., 2023; Sloan et al., 2022).

Against this background, this narrative review examines AI-supported remote monitoring in RA through three interlocking questions: what kinds of digital signals are currently being treated as clinically relevant, how patients engage with and experience the tools that generate those signals, and which implementation barriers continue to limit wider adoption. By bringing these strands together, the review seeks to move beyond a simple inventory of technologies and toward a more grounded account of what would be required for AI-enabled monitoring to become clinically useful, socially acceptable, and sustainable within routine RA care.

2. Methodology

2.1. Review design

We adopted a structured narrative review format because scholarship on AI-enabled remote monitoring in rheumatoid arthritis spans markedly different forms of evidence, including qualitative accounts, survey-based analyses, observational cohorts, feasibility pilots, service evaluations, exploratory machine-learning studies, and broader review papers. In a field this heterogeneous, thematic synthesis was considered better suited than quantitative pooling. The purpose of the review was therefore not to derive a single summary estimate, but to examine how digital monitoring tools are being used, what types of clinically relevant signals they generate, how patients and clinicians interpret them, and which conditions appear to support or hinder their translation into routine care.

The review was designed around three analytic domains that emerged as particularly relevant to the question of remote RA monitoring. The first domain concerned signal generation: which types of patient-generated data are being collected, and how AI or data-analytic methods are used to derive clinically meaningful information from them. The second concerned patient experience and engagement: whether users find these tools acceptable, understandable, and worth sustaining over time. The third concerned implementation context: the organizational, ethical, and social conditions that influence whether remote monitoring becomes part of real clinical pathways. This tripartite framing was intended to preserve the clinical relevance of the review while remaining consistent with the broader technology-and-society orientation of the target journal.

2.2. Search strategy

A focused PubMed search was conducted from database inception to March 2026. Search terms combined concepts related to rheumatoid arthritis, artificial intelligence, machine learning, remote monitoring, digital biomarkers, wearables, smartphone applications, mobile health, telemedicine, electronic patient-reported outcomes, patient engagement, usability, adherence, implementation, and barriers. The intention was to capture literature that addressed either the technical generation of remote disease signals or the human and organizational factors that shape their use. Search results were supplemented by manual screening of the reference lists of key review articles and influential primary studies in order to identify additional relevant reports and conceptually important papers that might not be retrieved by a single-string search.

Because terminology in this field is inconsistent, the search strategy was deliberately broad. Studies of interest do not always use the phrase remote monitoring even when they describe longitudinal data capture outside the clinic. Likewise, digital biomarkers may be discussed under the language of wearables, passive sensing, activity tracking, symptom reporting, or patient-generated health data. AI-focused studies may be labeled as machine learning, prediction modeling, hidden Markov modeling, random forest classification, or simply data analytics. The search therefore prioritized sensitivity at the screening stage and relied on thematic relevance during full-text assessment. Only English-language articles were included in the present review.

2.3. Eligibility criteria

Studies were eligible for inclusion if they focused on RA or RA-dominant inflammatory rheumatic populations and contributed to at least one of the core review domains: AI-supported analysis of remote data, digital biomarkers relevant to disease activity or flare monitoring, app-based or wearable-enabled remote follow-up, patient engagement and usability in digital monitoring, or barriers to implementation in routine care. Original quantitative studies, mixed-methods studies, qualitative studies, feasibility and pilot studies, and selected review articles were included when they directly informed the aims of the review.

Studies were excluded if they focused exclusively on imaging-based artificial intelligence without a remote monitoring component, on treatment-response prediction unrelated to longitudinal follow-up, on laboratory-only or omics-based diagnostic models, or on non-RA populations without clear relevance to RA monitoring pathways. Conference abstracts without sufficient methodological detail, editorials without original data or substantive synthesis, and non-English publications were also excluded. Review articles were used mainly for background, conceptual framing, and reference mining, whereas primary studies were prioritized when summarizing current evidence.

2.4. Study selection and data extraction

Titles and abstracts retrieved through the search strategy were screened for thematic relevance. Full texts were then reviewed for studies that addressed the capture, interpretation, or implementation of remote data in RA care. For each included article, data were extracted on study design, country and setting where available, population characteristics, type of digital tool or platform, kind of data collected, analytical or AI method used, major findings, and limitations that were relevant to the present review question. Particular attention was paid to whether a study generated new evidence on remote disease activity monitoring, whether it provided information on user experience or clinician workflow, and whether it offered transferable lessons for implementation beyond a single pilot setting.

The final corpus was intentionally selective rather than exhaustive. Because this review sought to build an integrated argument about AI-supported monitoring rather than compile every digital rheumatology intervention ever published, emphasis was placed on studies that were especially informative for the three focal domains of signal generation, patient engagement, and implementation. In practice, this meant that a smaller number of studies were discussed in greater depth, while broader reviews were used to contextualize the field and identify recurring themes.

2.5. Data synthesis

No quantitative pooling was performed because the included literature varied substantially in study aims, technologies, data sources, outcome definitions, and analytic methods. Instead, a narrative thematic synthesis was undertaken. Studies were grouped into categories that reflected the main stages of an AI-supported remote monitoring pathway: the production of longitudinal patient-generated data, the translation of those data into potentially meaningful disease signals, the interaction of patients with monitoring tools, and the embedding of these tools into service delivery. This approach made it possible to compare not only technical findings but also the practical conditions under which those findings might matter.

The synthesis was guided by a pragmatic question: what would have to be true for AI-supported remote monitoring to be useful in routine RA care? Studies were therefore interpreted not only in terms of whether they reported promising analytic performance, but also in relation to burden, actionability, interpretability, equity, workflow consequences, and the need for hybrid rather than purely digital care pathways. This perspective informed the organization of the Results and Discussion sections that follow.

Box 1. Core PubMed search domains used in the narrative review.

("rheumatoid arthritis" OR RA) AND ("artificial intelligence" OR AI OR "machine learning") AND ("remote monitoring" OR telemonitoring OR "digital biomarker*" OR wearable* OR smartphone OR "mobile app*" OR mHealth OR ePRO* OR telemedicine OR "patient engagement" OR adherence OR usability OR implementation OR barriers).

The search was supplemented by manual reference screening of key review articles and influential primary studies.

3. Results and interpretive synthesis

3.1. Overview of the reviewed literature

The literature included in this review depicts a field in transition. Early work in digital rheumatology focused largely on feasibility—whether patients would use apps, whether activity could be tracked, and whether remote data could be collected at all. More recent studies have started to ask more consequential questions about interpretation, service integration, and real-world value. As a result, the evidence base now spans systematic and scoping reviews, qualitative studies, surveys, feasibility studies, observational cohorts, mixed-methods service evaluations, and exploratory AI analyses. Taken together, these studies suggest that remote monitoring in RA is moving from isolated digital experiments toward more connected models of longitudinal, patient-generated assessment, although the methodological maturity of the field remains uneven (Davergne et al., 2020; Seppen et al., 2020).

Table 1. Selected studies underpinning AI-supported remote monitoring of rheumatoid arthritis.

Study	Design / data source	Digital component	Main contribution to this review
Curtis et al. (2022)	Longitudinal observational analysis; repeated PROs linked to physician-derived disease activity	Machine learning on repeated PROs	Demonstrated that longitudinal PRO data can classify low disease activity with clinically useful performance.
Rao et al. (2023)	Longitudinal observational study using Fitbit data and self-reported health scores	Wearables plus temporal machine-learning models	Showed that passive activity-tracker data can support classification of patient-reported health status over time.
Gossec et al. (2019)	Prospective observational ActConnect study	Wearable step-count data plus machine learning	Supported physical activity change as a candidate digital biomarker for flare-related worsening.
Gandrup et al. (2022)	Smartphone app study using daily symptom reporting	Daily patient-generated symptom data	Showed that higher symptom levels and steeper symptom slopes preceded self-reported flares.
Gandrup et al. (2024)	Exploratory machine-learning analysis of daily app data	App-based flare classification	Suggested that daily smartphone data may be useful for automated classification of flare weeks.

Study	Design / data source	Digital component	Main contribution to this review
Austin et al. (2020)	Proof-of-concept integration study	Smartphone monitoring integrated into the EHR	Highlighted workflow integration and the value of visualizing longitudinal data during consultations.
Watson et al. (2024)	Mixed-methods evaluation across six hospitals	Service-level remote monitoring pathway	Showed that implementation success depends on engagement, staffing, and pathway redesign.
White et al. (2021)	Qualitative study of patient perspectives	Remote measurement priorities and user expectations	Clarified that symptom fluctuation, fatigue, pain, and everyday impact matter to patients in digital monitoring.
Knitza et al. (2020)	Rheumatology survey study	Usage, preferences, barriers, and eHealth literacy	Showed the gap between general smartphone use and actual adoption of condition-specific digital tools.
Hider et al. (2023) / Sloan et al. (2022)	Survey and mixed-methods telemedicine studies	Digital inclusion, confidence, acceptability, and trust	Demonstrated that equity, perceived accuracy, and relational factors shape adoption.
Benavent et al. (2025)	Cocreation and feasibility study of IMIDoc	Integrated platform with ePROs, alerts, reminders, and clinician dashboard	Illustrated how remote monitoring can be embedded into a broader digital care architecture.

Abbreviations: EHR, electronic health record; PROs, patient-reported outcomes.

3.2. Longitudinal patient-reported outcomes as machine-readable disease signals

One of the most important developments in this literature is the demonstration that repeated patient-reported outcomes can be algorithmically informative rather than merely descriptive. Curtis et al. analyzed longitudinal PRO data from patients initiating a new biologic and showed that machine learning models could classify physician-derived low disease activity with clinically useful performance. The practical importance of this finding lies less in the exact model selected than in the broader proof of principle: data collected directly from patients over time can be structured in a way that helps recover clinically meaningful information even when joint examination or formal visit-based scoring is not immediately available (Curtis et al., 2022).

This use of PROs is important because it begins to reframe questionnaires from static measures of burden into dynamic signals of disease control. Repeated ratings of pain interference, physical function, patient global health, fatigue, or participation are not interchangeable with physical examination, but they can provide continuity between visits and may surface changes that are otherwise invisible to clinicians. Studies of daily symptom reporting further suggest that temporal pattern matters as much as symptom level. In other words, not only the presence of symptoms but also the direction, slope, and clustering of change may be informative. This longitudinal logic is central to remote monitoring and helps explain why AI methods become more valuable as data become denser and more temporally structured (Curtis et al., 2022; Gandrup et al., 2022).

3.3. Wearables and passive data as candidate digital biomarkers

Wearable devices offer a different but complementary route to remote monitoring because they can capture data passively and at relatively low user burden. In RA, the most studied passive signal has been physical activity, typically operationalized through step counts or related movement metrics. Rao et al. demonstrated that activity-tracker data could be used to classify self-reported health status and that a temporal modeling approach outperformed a simpler random forest classifier, suggesting that the sequence and evolution of data over time contain information that may be lost in more static summaries (Rao et al., 2023). This finding is notable because passive data can continue to accumulate even when patients are not actively completing questionnaires.

The most compelling evidence for physical activity as a candidate digital biomarker comes from work linking declines in activity to patient-reported flares. In the ActConnect study, wearable-derived activity data showed strong discriminatory potential for flare-related states, supporting the view that changes in everyday movement may reflect clinically relevant worsening for at least some patients (Gossec et al., 2019). At the same time, the wearable literature remains appropriately cautious. Reviews emphasize concerns about device accuracy, missing data, adherence over longer follow-up, and the fact that step counts are context-dependent: they may change because of work patterns, injury, weather, caregiving responsibilities, or non-inflammatory comorbidity as well as because of RA activity. Passive data therefore appear promising not as standalone disease measures, but as low-burden contextual signals that gain value when interpreted together with symptom reports and clinical context (Davergne et al., 2020; Rao et al., 2023).

3.4. Smartphone apps, electronic patient-reported outcomes, and flare-sensitive self-monitoring

Smartphone-based monitoring extends the logic of longitudinal measurement by allowing patients to record symptoms in real time or near real time. Compared with conventional questionnaires administered at clinic appointments, app-based self-monitoring can capture short-term variability, day-to-day symptom burden, and patterns that precede worsening. Gandrup et al. showed that self-reported flare weeks were associated with higher symptom levels and steeper symptom slopes in the days beforehand, suggesting that the micro-dynamics of patient-generated data may help characterize flare trajectories rather than simply documenting them after the fact (Gandrup et al., 2022).

A later machine-learning analysis of the same REMORA app dataset extended this work by showing that daily patient-generated data could be used to classify self-reported flares with encouraging discriminatory performance (Gandrup et al., 2024). These app-based studies are especially important because they demonstrate that remote monitoring can be temporally fine-grained without being restricted to passive sensing alone. They also illustrate a broader methodological point: active and passive data streams serve different functions. Daily symptom reports preserve subjective meaning and symptom nuance, whereas passive data reduce user burden and may reveal behavioral correlates of disease that patients would not routinely report. The reviewed literature increasingly suggests that the most informative remote monitoring systems are likely to combine both forms of data rather than privileging one at the expense of the other.

3.5. Integration into clinical workflows and service redesign

The reviewed studies also make clear that the value of remote monitoring depends on whether patient-generated data can be turned into something clinically usable. Austin et al. demonstrated that smartphone-derived data could be integrated into the electronic health record and used to provide clinicians with a broader visual account of symptom patterns over time. Participants in that study described this longitudinal view as offering the bigger picture of RA rather than a single visit-based summary, highlighting that digital monitoring may improve communication as much as measurement (Austin et al., 2020).

More service-oriented evidence comes from pathway evaluations in which remote monitoring formed part of a redesigned follow-up model rather than a standalone research tool. Watson et al. reported that a remote monitoring service for patients in remission or low disease activity could achieve meaningful patient engagement across multiple hospital sites, although staff experience was more mixed and pathway sustainability depended on local service conditions, staffing, and escalation processes (Watson et al., 2024). Similarly, the IMIDoc platform described by Benavent et al. illustrates the importance of cocreation and iteration. Although not limited to RA, the platform combined patient recording, medication support, educational content, alerts, and a clinician-facing dashboard, thereby moving remote monitoring from isolated data capture toward an integrated digital service architecture (Benavent et al., 2025).

3.6. Patient engagement, usability, and adherence

Across the reviewed literature, patient engagement emerged not as a minor implementation detail but as a central condition for effectiveness. White et al. found that patients valued remote measurement when it reflected the aspects of disease that mattered most in daily life, including pain, fatigue, mobility, variability, and triggers (White et al., 2021). This suggests that engagement is strengthened when monitoring is experienced as meaningful and personally relevant rather than as an administrative task. The same principle is echoed in studies of mHealth more broadly, where heterogeneity in uptake and outcome appears closely linked to how burdensome, understandable, and useful a digital tool feels over time (Seppen et al., 2020).

Survey evidence further indicates that readiness for digital monitoring cannot be assumed simply because patients own smartphones or use the internet. In Knitza et al., many participants reported regular smartphone use and believed that medical apps could benefit their health, but actual use of rheumatologyspecific digital tools was much lower, suggesting a gap between general digital familiarity and condition-specific digital adoption (Knitza et al., 2020). The implication is that successful monitoring platforms must do more than exist; they must be discoverable, credible, easy to use, and sufficiently worthwhile for patients to sustain participation. Adherence is therefore shaped by interface quality, perceived benefit, trust, feedback loops, and the extent to which data entry can be balanced with passive sensing.

3.7. Equity, trust, and organizational readiness

The social and organizational dimensions of remote monitoring were recurrent themes in the literature. Hider et al. showed that digital exclusion remains a substantial issue in inflammatory rheumatic disease populations, with a non-trivial proportion of respondents lacking either access to internet-enabled devices or confidence in internet use, and with RA populations particularly affected in some analyses (Hider et al., 2023). These findings are important because they challenge the assumption that digital follow-up is a universally scalable solution. A technically effective tool may still deepen inequity if it is easiest to use for patients who are already well connected, technologically confident, and highly resourced.

Trust also emerged as a critical mediator of adoption. In Sloan et al., both patients and clinicians often appreciated the convenience of telemedicine but rated it as inferior to face-to-face care for accuracy of assessment and, in some cases, for relational aspects of care (Sloan et al., 2022). This tension matters for AI-supported monitoring because algorithmic recommendations or remote alerts will only be accepted if users believe that the system captures clinically relevant information and that appropriate human judgment remains in the loop. Organizational readiness is similarly crucial. Platforms require triage rules, staffing, escalation pathways, interoperability, and a clear understanding of who is responsible for reviewing data and acting on alerts. Without these features, digital monitoring risks creating new informational burdens without clear clinical benefit.

Table 2. Recurrent implementation barriers identified in the reviewed literature.

Barrier	Why it matters	Practical implication
Digital exclusion and literacy	Patients without internet-enabled devices, reliable connectivity, or digital confidence may be unable to participate fully in remote care.	Implementation plans should include inclusive onboarding, alternatives to app-only pathways, and monitoring for unequal uptake.
User burden and adherence	Frequent manual reporting can reduce long-term engagement and lead to missing data.	Blend active symptom reporting with passive sensing and provide feedback that makes participation feel worthwhile.
Trust and perceived accuracy	Patients and clinicians may regard remote assessment as less accurate than face-to-face review in some situations.	Use remote monitoring to target and enrich care rather than to indiscriminately replace in-person assessment.
Workflow integration	Incoming data, alerts, and dashboards can create new tasks if roles and escalation pathways are unclear.	Specify who reviews data, how alerts are triaged, and when remote findings trigger clinician contact or in-person care.
Interoperability and data governance	Data that remain outside routine records or lack clear governance can be difficult to use safely and consistently.	Integrate monitoring outputs into routine documentation systems and define responsibility for data review and action.
Equity and service design	One-size-fits-all digital pathways may advantage stable, digitally confident patients while disadvantaging others.	Use hybrid pathways with selective intensity and preserve alternatives for patients who need or prefer conventional follow-up.

3.8. Cross-study synthesis

Across these studies, four patterns recur. First, the strongest signals are longitudinal rather than isolated; what matters most is not a single digital observation but how that observation changes over time. Second, passive data are attractive because they reduce reporting burden, yet they become more clinically interpretable when paired with symptom-based input. Third, digital usefulness depends on workflow: data create value only when they are seen, contextualized, and linked to action. Fourth, the social preconditions of adoption—trust, inclusion, literacy, and perceived relevance—are not external to implementation; they are part of the intervention itself. These recurring patterns help explain why the field is gradually shifting from enthusiasm about tools to deeper questions about care design.

4. Discussion

4.1. Principal interpretation

The central conclusion of this review is that AI has its clearest value in RA not as a substitute for clinical judgment, but as an interpretive layer for longitudinal patient-generated data. The reviewed studies consistently indicate that the meaningful unit of digital monitoring is not the isolated data point, but the evolving pattern: repeated patient-reported outcomes, trends in activity, day-to-day symptom trajectories, and the relationship between those signals and clinical context. In this sense, AI is most useful when it helps convert accumulation into interpretation, organizing what happens between visits into information that can support triage, discussion, or timely review.

4.2. Comparing active and passive monitoring modalities

A particularly useful way to interpret the literature is to compare active and passive modes of monitoring. Active monitoring, such as app-based symptom reports or repeated PROs, has the advantage of preserving subjective experience. It captures pain, fatigue, stiffness, and functional disruption in the patient's own terms and can therefore remain closely aligned with what matters clinically and personally. Passive monitoring, by contrast, reduces the burden of repeated data entry and can generate continuous information about behavior or physiology without requiring constant effort. Neither approach is sufficient on its own. Active monitoring may be informative but burdensome; passive monitoring may be scalable but ambiguous without symptom context. The most plausible future direction is therefore multimodal monitoring in which active and passive signals are interpreted together rather than separately (Gossec et al., 2019; Rao et al., 2023; White et al., 2021).

This distinction also has implications for model design and for patient acceptance. If a system relies entirely on self-report, engagement may decline over time as monitoring becomes repetitive or intrusive. If it relies entirely on passive signals, users may struggle to see how the data reflect their actual symptoms or may distrust the system when their subjective experience is not mirrored by an algorithmic output. Hybrid approaches can potentially mitigate both problems: they preserve patient voice while using passive data to reduce burden and fill temporal gaps. For this reason, multimodal monitoring is not simply a technical upgrade; it is also a patient-centered design strategy.

4.3. From digital signal to clinically meaningful biomarker

The literature reviewed here also invites caution about the language of digital biomarkers. The term is attractive because it suggests objectivity and clinical precision, yet many candidate signals in RA remain at an intermediate stage between exploratory digital correlate and validated clinical biomarker. A decline in steps, a change in activity rhythm, or a cluster of daily symptom scores may indicate worsening for a given patient, but these signals are not yet universally interpretable across settings or populations. Their meaning depends on context, baseline behavior, comorbidity, seasonality, work demands, and how the data are collected. A clinically meaningful digital biomarker should therefore be understood not simply as any measurable remote signal, but as a signal that is interpretable, sufficiently stable, linked to patient-important outcomes, and actionable within care pathways (Davergne et al., 2020; Gossec et al., 2019).

This actionability point is essential. The goal of remote monitoring is not the accumulation of data for its own sake, but the creation of information that can support triage, discussion, self-management, or treatment decisions. A monitoring signal becomes valuable when it changes what patients or clinicians do. Current studies offer promising examples of this transition, especially where longitudinal data are visualized in consultations, used to support escalation pathways, or embedded within digital platforms that include messaging and alerts. However, much of the evidence base still sits at the level of feasibility rather than demonstrated clinical action. Future work should therefore pay closer attention to thresholds for intervention, false-positive burden, alert fatigue, and the downstream consequences of acting or not acting on remote signals (Austin et al., 2020; Benavent et al., 2025; Watson et al., 2024).

4.4. Patient-centered design, trust, and sustained use

A second major interpretation from this review is that patient engagement is not external to the success of AI-supported monitoring; it is one of its core mechanisms. Monitoring systems only produce meaningful longitudinal data when patients can and will use them over time. The literature suggests that sustained use is more likely when tools align with patients' priorities, minimize effort, provide feedback that feels relevant, and operate within a relationship of trust. Qualitative work makes clear that patients want remote monitoring to capture the instability and everyday impact of disease, not merely to reproduce narrow biomedical indicators (White et al., 2021). Survey evidence further suggests that condition-specific app use remains low even in digitally connected populations, underscoring the difference between general smartphone familiarity and willingness to adopt health technology for chronic disease management (Knitza et al., 2020).

Trust has several layers in this context. Patients must trust that their data are secure, that the effort of contributing data is worthwhile, and that the outputs will be reviewed or acted upon appropriately. Clinicians must trust that the information is sufficiently valid and clinically relevant to justify incorporating it into decision-making. If either party doubts the usefulness or safety of the system, adoption may stall. This helps explain why convenience alone is not enough to guarantee uptake. Even where remote care is valued for reducing travel and making contact easier, concerns about accuracy, depersonalization, or inappropriate substitution for face-to-face assessment can persist (Sloan et al., 2022).

4.5. Equity and implementation realities

From an implementation perspective, the most striking lesson is that the hard problem is rarely data collection alone. Remote monitoring enters real services shaped by staffing constraints, variable digital access, privacy expectations, clinical uncertainty, and uneven confidence in remote care. A technically capable system may still fail if it produces too much unfiltered data, reaches the wrong patients, or demands new work without clarifying who acts on what. The adoption question is therefore as much organizational and social as it is computational.

Implementation is also a matter of workflow and responsibility. Remote monitoring generates tasks: someone must review incoming data, triage alerts, contact patients, document decisions, and decide when remote findings warrant in-person assessment. If these tasks are not explicitly allocated, digital systems may increase hidden workload or produce information that is never meaningfully used. The more promising studies in this review were precisely those that moved beyond isolated data collection toward service redesign, EHR integration, clinician-facing dashboards, or cocreated platforms in which patients, clinicians, and developers jointly shaped the monitoring pathway (Austin et al., 2020; Benavent et al., 2025; Watson et al., 2024). These examples suggest that remote monitoring should be designed as a pathway rather than as a device or app.

4.6. A practical roadmap for hybrid remote monitoring

The most plausible future, therefore, is a hybrid rather than fully automated model of care. In such a model, AI does not replace the clinician or the patient's narrative; instead, it helps structure longitudinal signals so that both become more informative. Remote monitoring is then used to enrich care pathways—prioritizing review, supporting shared decision-making, and allowing low-burden follow-up when disease is stable—while preserving rapid access to in-person care when complexity or uncertainty rises.

A practical roadmap for hybrid monitoring would include several design principles. First, remote systems should combine active and passive data wherever feasible so that symptom meaning and behavioral context are captured together. Second, they should provide visible feedback to patients and clinicians rather than functioning as opaque data collection tools. Third, inclusion strategies should be built in from the beginning, including alternatives for those with limited digital access or literacy. Fourth, implementation should include clear governance regarding data review, responsibility, and escalation. Finally, evaluation should extend beyond model accuracy to include usability, adherence, workload, equity, and patient-perceived value. These principles align with the cocreation logic of platforms such as IMIDoc and with service-level lessons from EHR-integrated monitoring and multi-site remote follow-up pathways (Austin et al., 2020; Benavent et al., 2025; Watson et al., 2024).

Table 3. Practical design principles for AI-supported hybrid monitoring in rheumatoid arthritis.

Design principle	Why it matters	Example operationalization
Combine active and passive monitoring	Subjective symptom meaning and low-burden behavioral continuity are both important.	Pair daily or weekly symptom prompts with wearable-derived activity trends rather than relying on either source alone.
Keep a clinician in the loop	Remote signals become clinically useful when they lead to review, triage, or discussion.	Use dashboards, escalation rules, and scheduled clinician review of flagged patterns.
Design for inclusion from the start	Digital tools that ignore access and literacy may increase inequalities in care.	Offer onboarding support, multiple contact modes, and non-digital alternatives where appropriate.
Make outputs understandable	Opaque monitoring systems are harder for both patients and clinicians to trust.	Provide simple trend visualizations, symptom summaries, and transparent explanations of what alerts mean.
Evaluate beyond accuracy	A technically strong model may still fail if it creates burden or does not fit workflow.	Track adherence, usability, workload, equity of access, and patient-perceived value alongside analytic performance.
Build remote monitoring as a pathway	Sustainable benefit depends on service redesign rather than on standalone apps.	Define response responsibilities, integrate with records, and align monitoring with triage and follow-up processes.

4.7. Limitations of the evidence base, limitations of this review, and future directions

This review must be interpreted alongside the limitations of the current evidence base. Many studies in digital rheumatology remain small, exploratory, or feasibility-oriented. Outcome definitions vary, monitoring intervals are inconsistent, and external validation is still uncommon. Studies also differ in whether they evaluate symptom burden, physician-derived disease activity, flare, service outcomes, or user experience, making direct comparison difficult. In addition, the strongest evidence often comes from motivated patient groups who are willing to use apps or wearables, which may overestimate acceptability in more diverse routine populations. These limitations do not negate the promise of AI-supported monitoring, but they do caution against premature claims of readiness for universal scale-up (Momtazmanesh et al., 2022; Seppen et al., 2020).

The present review also has limitations. It relied on a single database, was limited to English-language publications, and used a structured narrative rather than systematic review design. As a result, the synthesis was selective and interpretive. This was appropriate for the aim of integrating technical, patient-centered, and implementation themes, but it means that the review should not be read as an exhaustive inventory of all digital RA studies. The emphasis on a smaller number of conceptually informative articles was deliberate, yet different selection decisions might have produced somewhat different emphases.

Future research should therefore proceed along several lines. Technically, there is a need for larger and more diverse datasets, stronger external validation, multimodal models that integrate subjective and passive data, and more transparent reporting of model development and performance. Clinically, studies should examine whether remote signals change decision-making, reduce delays in response to worsening, or improve patient-important outcomes. From a social and implementation perspective, future work should measure usability, burden, digital inclusion, trust, and impact on staff workload with the same seriousness accorded to analytic accuracy. Pragmatic trials and implementation studies that explicitly compare hybrid care pathways with conventional follow-up may be especially valuable. In short, the next phase of digital rheumatology should move beyond asking whether AI can detect patterns in remote data and toward asking when, for whom, and under what conditions such detection improves care in a way that is equitable and sustainable.

5. Conclusions

This review argues that the future of AI-supported monitoring in rheumatoid arthritis lies less in replacing clinical assessment than in making the periods between visits more visible, intelligible, and actionable. The most convincing evidence to date comes from systems that learn from repeated patient-generated data—patient-reported outcomes, wearable-derived activity patterns, and smartphone-based symptom reports—rather than from isolated digital measurements. These tools can enrich conventional care by making fluctuations in pain, fatigue, function, and flare dynamics easier to detect over time. However, digital biomarkers in RA remain an evolving construct, and their usefulness depends on interpretation, clinical context, and integration into care pathways rather than on data capture alone.

The literature also shows that implementation is fundamentally a human and organizational challenge. Patient engagement, trust, digital literacy, privacy, equity, and workflow design are not peripheral considerations; they are the conditions under which technical promise becomes clinical value. For that reason, the most realistic path forward is a hybrid model in which AI helps organize longitudinal signals, while clinicians retain interpretive oversight and patients remain active partners in monitoring. Future research should prioritize multimodal and externally validated models, longer follow-up, explicit attention to digital exclusion, and implementation studies embedded in real-world care settings. In this sense, the question is no longer whether remote monitoring in RA is possible, but how it can be made trustworthy, equitable, and genuinely useful.

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