Wearable activity trackers and artificial intelligence in the management of rheumatic diseases

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Wearable Activity Trackers and Artificial Intelligence in the Management of Rheumatic Diseases, Where are We in 2021?

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Keywords: wearable activity trackers; disease flares; remote monitoring; rheumatic disease, artificial intelligence

Article Type: Leitthema

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

The total length: 38,167 characters (including spaces, references, tables and legends to figures)

Abstract:

Wearable activity trackers are playing an increasingly important role in healthcare. In the field of rheumatic and musculoskeletal diseases (RMDs), various applications are currently possible. This review will present the use of activity trackers to promote physical activity levels in rheumatology, as well as the use of trackers to measure health parameters and detect flares using artificial intelligence. Challenges and limitations of the use of artificial intelligence will be discussed, as well as technical issues when using activity trackers in clinical practice.

Abstrakt:

Wearable Activity Tracker spielen eine immer wichtigere Rolle im Gesundheitswesen. Im Bereich der rheumatischen und muskuloskelettalen Erkrankungen (RMDs) sind derzeit verschiedene Anwendungen möglich. In dieser Übersichtsarbeit wird der Einsatz von Aktivitätstrackern zur Förderung des körperlichen Aktivitätsniveaus in der Rheumatologie vorgestellt, sowie der Einsatz von Trackern zur Messung von Gesundheitsparametern und zur Erkennung von Krankheitsschüben mittels künstlicher Intelligenz. Herausforderungen und Grenzen des Einsatzes von künstlicher Intelligenz werden ebenso diskutiert wie technische Fragen beim Einsatz von Aktivitätstrackern in der klinischen Praxis.

1. Introduction

All areas of our lives are influenced by digitalization. Recent progress is modifying how health data are collected. E-health encompasses traditional telemedicine, but also the use of connected devices or mobile applications, in a context of self-monitoring, or of continuous remote monitoring for research. The new fully digitalised world is also creating new epidemiological and statistical possibilities based on analysing massive and heterogeneous data, using artificial intelligence (AI).

In this review, we will present some of these new ways of collecting and analysing data, when applied to rheumatic and musculoskeletal diseases (RMDs). We will first discuss the uses of activity trackers in rheumatology that allow self-monitoring and feed-back to help patient for education purposes. Here specifically, we will address increasing physical activity, since RMD patients are at risk of inactivity. We will then summarise some of the potential uses of AI to analyse large data sets in RMDs. Recent applications of AI include analysing activity data to detect flares in inflammatory arthritis, as well as detecting structural damage progression on images, predicting response to biologic therapies or performing faster literature reviews on rheumatological topics.

Although digital health and AI are promising, various limits exist and will be addressed. Finally, technical issues of the use of activity trackers in clinical research will be presented.

2. Use of activity trackers for self-monitoring of physical activity

Wearable activity trackers are very popular. The new generation of activity trackers can provide information on a person's physical activity including the number of steps, the time spent inactive, intense versus moderate activity and even energy expenditure. These devices are generally linked with other devices such as a smartphone or computer, which allows this information to be displayed in the form of graphs and informative statistics.

This information could be used to educate and motivate users toward better physical activity habits and better health behaviour. One of the great advantages of wearable activity tracker is that physical activity is collected passively, automatically and continuously, offering remarkable possibilities for self-monitoring but also research.

This section will address the use of activity trackers for self-monitoring of physical activity since this subject is the most developed in rheumatology.

2.1. Physical activity

Physical activity is usually defined as “any bodily movement produced by skeletal muscles that results in energy expenditure”[1]. 150 minutes of physical activity are per week recommended. This is often approximated as 10000 steps per day. Active living is recommended at any age. It protects against many non-communicable diseases and reduces mortality. In patients suffering from osteoarthritis or chronic inflammatory rheumatic diseases, general exercise, aerobic activity, strength exercises or yoga sessions are linked to a significant reduction in pain, depression, disease activity and improvement in cardiovascular disorders, joint mobility and physical function [2].

Despite the benefits of physical activity, healthy people and patients are vulnerable in terms of physical activity levels. According to the World Health Organization in 2016, 23% of men and 32% of women aged over 18 were insufficiently physically active [3]. This is even lower for patients with inflammatory rheumatic diseases or osteoarthritis, with, for example, 1 in 4 adults reaching the recommendations for patients with spondyloarthritis in the United Kingdom [4].

2.2. Effectiveness of wearable activity trackers to promote physical activity

Several reviews have demonstrated the efficacy of trackers (Figure 1).

We performed a systematic review of interventions to increase regular physical activity with a wearable activity tracker in patients with RMDs (17 studies;1,588 patients) [5]. The results showed that short-term adherence to wearable activity trackers was high in this population (92% at 10 weeks). Activity trackers were found to increase physical activity levels by 1520 steps per day, when comparing the groups not using the tracker, over an average wearing time of 14 weeks (Figure 1). However, no significant results were found in prolonged follow-up (i.e., after stopping the use of the tracker). The increase in physical activity was not correlated with an increase in short-term symptoms, although pain increased during long-term interventions.

Another recent systematic review and meta-analysis, including 48 studies and involving 5,808 participants, evaluated the effectiveness of wearable activity trackers in increasing physical activity [6]. Half of the trials recruited participants with a medical condition, including among others, early knee osteoarthritis, rheumatoid arthritis and systemic lupus erythematosus. The other half of inclusions did not restrict participants by medical conditions. Use of wearable activity trackers improved daily steps with small to medium effects (mean difference: 1078 steps/day, 95% CI 772, 1384) and moderate to vigorous weekly physical activity (mean difference: 42 minutes/week, 95% CI 28, 57). However, no effect was found on light physical activity and sedentary behavior. One explanation could be that wearable activity trackers might be effective in improving conscious exercise behavior but not habitual behavior [6].

In another systematic review with meta-analysis evaluating the use of a physical activity tracker in cardiac rehabilitation participants, an increase of daily steps was found compared with controls (3 trials, n = 211, mean difference 2587, 95% CI, 916-5257]). More interestingly, a significant increase in aerobic capacity was found compared to controls [7]. These results are important since patients with inflammatory arthritis are more exposed to cardio-vascular risks.

Similar results were found in a recent systematic review of healthy subjects, where an increase of 1850 steps per day (95% CI 1247 - 2457) was found in groups using an activity tracker and smartphone app [8].

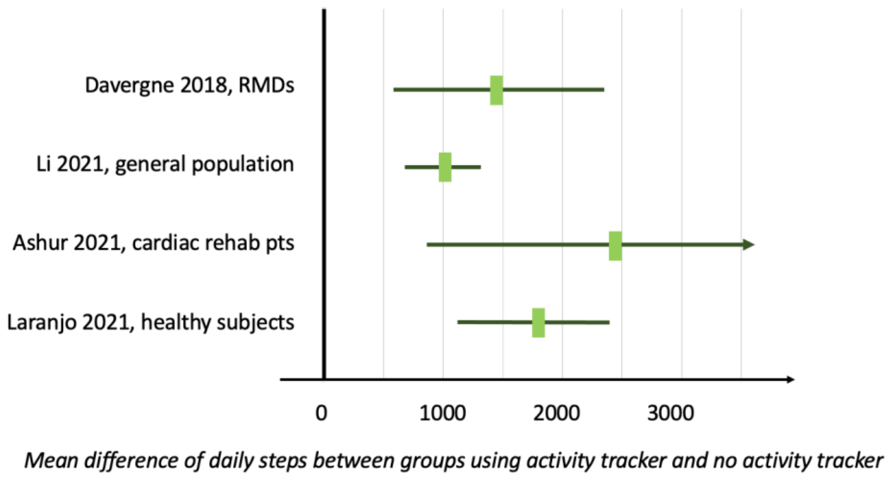

Figure 1: effectiveness of activity trackers to increase daily steps in various population. RMDs: rheumatic and musculoskeletal diseases, rehab pts: rehabilitation participants.

2.3. Moderators of effect in activity trackers

In one of the systematic reviews above [6], a meta-regression analysis was performed to identify potential moderators of effect size. Improvements in physical activity with the activity tracker were associated with some participant characteristics and some intervention characteristics. For example, a difference of approximately 40 minutes of moderate to vigorous physical activity per week was observed between men and women, approximately 27 minutes between a simple pedometer and a more advanced tracker using an accelerometer, and approximately 21 minutes between intervention durations greater or less than 12 weeks. Other relevant participant characteristics were age, health status, and baseline physical activity level. Other intervention characteristics were modes of expert support. Interestingly, face-to-face delivery of information with a human was no better than an automated computer message. Participants with medical conditions achieved a higher increase in moderate to vigorous physical activity compared to participants without medical conditions (approximately 26 minutes. These results will help to select the patients most likely to benefit from the trackers.

In another systematic review exposed above [8], subgroup analysis and metaregression of behavior change techniques used reveal that interventions using activity trackers were significantly more effective when including text messaging and personalization features.

In conclusion, although effects of activity trackers appear to be modest, a large effect at the population level could be expected given the wide and increasing reach of wearable devices and smartphones. Future programmes using activity trackers to increase activity levels should use more advanced activity trackers for longer than 12 weeks, including text messaging and personalization features. Such programmes should target in priority men with medical conditions.

3. Activity trackers to monitor disease activity using AI in inflammatory arthritis

AI allows the analysis of Big Data such as data at the level of the minute from physical activity monitoring using activity trackers.

Inflammatory arthritis such as rheumatoid arthritis or axial spondyloarthritis are marked by frequent flares even in patients with well-controlled disease. These fluctuations in disease activity have deleterious consequences in the short and long-term, and assessing flares is important in clinical practice. Activity trackers allow passive continuous data collection. We performed a study applying AI to activity data, to detect flares, which we will review here [9].

3.1. Detecting flares by activity trackers: the ActConnect Study

The basis of our study was that physical activity and in particular walking and activity patterns may be influenced by flares. Physical activity can be objectively measured using activity trackers. Thus, we hypothesized that activity trackers could be used in the assessment of disease flares. [9–11].

We performed a 3 months longitudinal observational study named the ActConnect study in 2018, of 157 patients with either rheumatoid arthritis or axial spondyloarthritis. Patient-reported flares were assessed weekly through the patient's smartphone by asking a dedicated question: "Has your disease flared up since the last assessment?", with a categorical response according to no flare, flare lasting 1–3 days (short flare) or flare lasting more than 3 days (persistent flare). Physical activity was collected continuously using a connected activity tracker (Withings® Activity Pop watch) over the 3 months.

Most of the 170 patients had long-standing disease and around half of them were receiving a biologic therapy. Although the disease appeared well-controlled, we found that flares were frequent: patients reported having experienced a flare on average in 28% of the weekly assessments. Short flares were more frequent than persistent flares, corresponding to 26 flares for 100 patient-weeks [11].

The mean number of steps per day over 3 months was 7124 (standard deviation: 2316) corresponding to 108 (36) minutes per day of moderate to vigorous activity. Thus, physical activity was moderate overall, with 24-30% of patients fulfilling the World Health Organization recommendations for physical activity [10,12].

In a first analysis, the relationship between physical activity and disease activity was assessed using linear mixed-effect models. We found that persistent flares were related to a moderate decrease in physical activity [11]. At the group level, there was a relative decrease in physical activity of 12-21% during weeks with flares, corresponding to an absolute decrease of 836-1462 steps per day [10]. However, using standard statistics, we were unable to find a precise cutoff value allowing to detect flares based on steps.

3.2 Use of machine learning to detect flares

In a second phase, we analysed the link between patient-reported flares and activity-tracker-provided steps per minute (and not mean steps per day) using AI by machine-learning using selective (multiclass) naive Bayesian statistical methods [9]. Machine learning allows analyses of huge amounts of data with minimal aggregation of data. It is remarkable that the machine learning model detected correctly both patient-reported flares and absence of flares with a sensitivity (the ability of a test to correctly classify an individual as flaring) of 96% and a specificity (the ability of a test to correctly classify an individual as not flaring) of 97% [13]. The corresponding positive and negative predictive values were respectively 91% and 99%.

This study is one of the first to demonstrate the usefulness of machine-learning applied to large rheumatology datasets [14]. We believe the next years will see an explosion in such analyses.

4. Other examples of AI in rheumatology

Activity trackers are far from being the only applications of AI in rheumatology. Indeed, as AI encompasses various methods of data analysis, it can be applied to different fields in rheumatologists' daily practice.

Imaging is one of the fields that benefit the most from the advances of AI methods. Indeed, machine learning methods such as artificial neural networks enable an automatic analysis of images, with different levels of interpretation of the findings (fully-human, semi-automatic interpretation or fully-automatic interpretation) [15]. In RA, such methods have been applied to identify and quantify synovitis or tenosynovitis on MRI or ultrasonography [16], and to detect bone erosions on hand radiographs [17]. In axial spondyloarthritis, machine learning methods related to so called "computer vision" enable comparisons between MRI images in a same patient, and subsequently display the changes over time by image subtraction and color coding (Figure 2) [18]. In osteoporosis, machine learning methods were used to predict the occurrence of jaw osteonecrosis and bone density loss, based on dental panoramic radiographs [19,20].

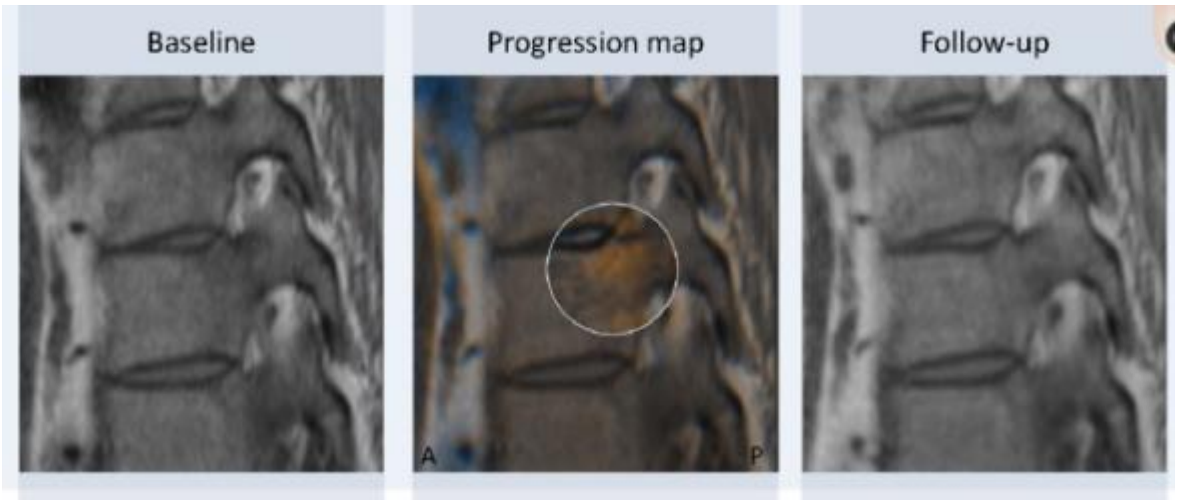

Figure 2: comparative imaging of a spine MRI in a patient with axial spondyloarthritis (Aizenberg et al [18]).

AI methods may also be used to identify prognostic factors and predict outcomes in rheumatic diseases. Thus, a Dutch team elaborated a model predicting flares in RA patients, using random forests applied to demographic, clinical, laboratory and medication data recorded in an Electronic Medical Register. This model had good predictive performances, with a mean AUC of 0.8 [21]. A regression model based on Gaussian processes, and taking into account clinical, demographic and genetic data, was used to predict the response to anti-TNF therapy after methotrexate failure in a dataset of 1892 American RA patients. This model displayed an accuracy of 78% [22].

AI may also be a helpful and time-sparing tool to perform systematic literature review on rheumatic topics. A French team developed BIBOT, a software based on natural language processing methods, to perform a systematic literature review on cutaneous manifestations of primary Sjögren's syndrome; BIBOT was much faster than manual search and automatically classified the articles of interest in a chart. Reliability of this tool was good, given that among 202 relevant articles, 155 (77%) were selected by both AI and manual method [23].

Thus, the implementation of AI tools in rheumatologists' daily practice may have a benefic impact on patients' assessment and follow-up, therapeutic decision making, research and physicians' further education.

6. Practical use of activity tracker in clinical research

6.1. Pooling activity monitoring in epidemiological research

Wearable activity trackers could represent a valuable source of physical activity data for epidemiological research, especially due to their widespread use and the long-term nature of the recorded data. In order to record and collect physical activity data from different consumer activity tracker vendors, new solutions are emerging. These solutions aim to solve the problems caused by the large heterogeneity between activity tracker models in terms of the types of data available, the accuracy of the recorded data and the sharing of data between different vendors and third-party systems. Using data from the device that patients already have is useful, but it is not clear that measures of activity, sleep and other behaviours are comparable across devices, and it can be difficult to standardise the collection, collation and processing of data across different devices.

Once the data from the mobile sensors is collected from the patients, the ideal situation would be a seamless integration with the electronic medical records. This would allow therapists to access patient data directly. To ensure proper interpretation, training would probably be required for the medical staff. This transferability of data from sensors to electronic medical records has already been tested in oncology, with encouraging results [24].

The translation of raw data into digital biomarkers requires strategic choices and most of the time multidisciplinary collaboration. The volume of continuously collected sensor data can be enormous. One solution may be to use the tracer software for data reduction, such as the calculation of the number of daily steps or the average resting heart rate. However, proprietary algorithms can be mostly opaque [25].

In order to face the challenges from the large heterogeneity between activity tracker models in terms of available data types, the accuracy of recorded data, and how this data can be shared between different providers and third-party systems, innovative systems are emerging. One example is the mSpider system, which is a working prototype currently capable of recording physical activity data from consumer activity tracker vendors. This experimental system automatically records physical activity, energy expenditure, pulse, sleep etc., from participants wearing activity trackers from Apple, Fitbit, Garmin, Oura, Polar, Samsung and Withings, as well as trackers storing data in Google Fit and Apple Health. Three modules make up this system: (1) the web front-end, (2) the server back-end, and (3) the mobile application. The web front-end is used when accessing their activity tracker data to manage surveys and facilitate participant authorisation. The server back-end stores participant authorisation access information, manages data transfer between mSpider and supported vendor cloud storages and stores uploaded activity tracker data. The mobile application further facilitates authorisation and data transfer for providers where communication cannot be made directly between the server back-end and the provider's cloud storage (e.g. Samsung and Apple activity trackers). For these providers, the communication is performed by the provider's mobile application and uploaded to the mSpider server back-end via the mSpider mobile application. One of the applications performed was the identification of changes in physical activity levels during COVID-19, showing that the mSpider system can be a valuable tool for collection of long-term data on physical activity, including historical data and detecting changes in physical activity over time [26].

Another example is the Remote Assessment of Disease and Relapses (RADAR)-base. RADAR-base is an open-source platform for collecting physical activity data from smartphones, Fitbit and Garmin activity trackers, and some research accelerometers. RADAR-base uses similar technology to mSpider, but data collection is limited to only two consumer activity tracker vendors. In a 2020 study, this system was also used to track daily steps during national lockdowns in chronically ill participants equipped with a Fitbit tracker [27].

In the future, these systems might solve interface problems with the practice software if their use is made accessible to health professionals.

6.2. Practice guides to use activity trackers in trials

Although activity trackers are increasingly used in clinical research, very few technical reports or best practice guides are published to help researchers design and conduct studies using activity trackers. In a recent study, a group of authors with prior experience in research using activity trackers described the key challenges and solutions associated with the use of Fitbit activity trackers. The challenges and solutions fell into four main categories: study preparation, intervention delivery, data management, and study closure. For example, to promote adherence to the tracker, the authors recommend choosing a device with a heart rate monitoring feature to calculate an approximate wear time. If the wear time is less than 10 hours per day, one option could be to send messages by research staff or create automatic SMS reminders to wear the tracker. Another example is to provide participants who are unfamiliar with tracker technology with a user manual tailored to their reading level to explain how to use the device and mobile app in the study setting. Another strategy outlined by the authors is to conduct orientation sessions on the tracker with study participants, consider a run-in period to allow participants to become familiar with the technology, or identify a superuser (e.g., a family member or research assistant) to assist and troubleshoot technology issues [28].

7. Discussion

7.1. Limits of activity trackers to self-monitor physical activity

Although activity tracker offers promising perspectives to increase physical activity level, various limits exist.

Adherence to activity trackers could be low, reducing the potential effect of the tracker. More than half of the participants stop using the activity tracker after two weeks and 75% after four weeks as showed in a study in undergraduate students [29].

Long-term effect of activity trackers in unclear. In a study with follow-up after the end of the intervention, no evidence of increase in steps after stopping wearing the wearable activity trackers was observed [30].

Health literacy and physical literacy may influence the interpretation of data collected by trackers. The concept of health literacy refers to the personal and relational factors that affect a person's ability to acquire, understand and use information about health and health services [31]. It has been shown that active people have a higher health literacy than inactive people. In addition to providing monitoring of activities to increase physical activity, a comprehensive approach could also focus on health and physical literacy.

Barriers and facilitators to physical activity should be adressed. In addition to the use of new technologies to increase physical activity, other aspects should be taken into consideration such as barriers and facilitators,and stages of behavior change for a global approach [32]. Regarding physical activity, barriers and facilitators have been identified. Barriers appear to be mostly related to psychological status such as fear of movement, and facilitators are linked in part to social support such as receiving encouragement to participate in physical activity or having a partner to play sports with [32].

7.2. Challenges and limits of AI in 2021

Although promising, AI methods have currently several limitations. First, most of these methods are based on supervised learning, which implies that large amounts of data are required to train the models properly. Moreover, these data must be accurate, so that the model does not learn from fallacious information and does not provide wrong conclusions. Consequently, a proper quality control of the data must be performed before the analysis, which can be long and laborious. Thus, even if AI methods mentioned previously may be time sparing for the physicians, the implementation of these methods in daily practice may be time consuming and costly.

Additionally, unlike the human brain, no AI method can solve a multitude of problems to date. Indeed, a model based on AI methods may only answer to one specific question, on the basis of a specific dataset. Human expertise and intervention are therefore still needed to choose the settings of the model, to train and validate it. However, evolutionary algorithms may help designing models in the future, in order to find the optimum parameters automatically [15].

Another issue is that, although promising on specific datasets, most of AI models does not pass external validation; consequently, even if the number of AI publications is still growing, only a few AI models are presently applied in clinical practice. Additional validation studies are therefore needed, but most of these studies mainly focus on "technical" performances of the models, and do not account for clinical relevance. Thus, a closer collaboration between data scientists and clinical researchers is crucial to implement AI tools in rheumatology practice; this point has been raised in the recent EULAR points to consider for the use of big data and AI in rheumatic diseases [33].

This collaboration is all the more important, given the complexity of AI methods. Indeed, some methods such as neural networks may be considered as "black boxes": these methods perform well for given tasks, but the process leading to the results remains unclear. Further studies are therefore required to make these algorithms more understandable. Beyond technical understanding of AI methods, there is also an ethical issue when it comes to health-related research. Indeed, given the potential consequences on patient's health, it seems essential to keep control over the explanation of the decision taken by the machine.

These limitations represent a challenge for research involving AI. To address these issues, a research agenda was proposed by EULAR, with several working points related to data collection, data analyses, training, interpretation, and implementation of findings [33]. The execution of this research agenda is ongoing.

7.3 Data protection and privacy

Privacy and data security is one of the main concerns regarding the use of wearable devices. Indeed, wearable technology encourages the collection, storage and sharing of health-related data, which may be perceived as more sensitive than the usual name, gender and age information. From an ethical point of view, it is necessary that users of sensors understand the risks and benefits of collecting and sharing this data. In addition, it seems necessary to promote the accessibility of sensors and their ease of use and interpretation among less sophisticated audiences [34]. However, these devices are associated with a risk to the security and privacy of consumers, as they process sensitive data such as level of physical activity and therefore health, location of journeys through GPS and their timing, heart rate etc. A famous example is the disclosure of US military bases by the Strava application [35]. In terms of data protection policy, each country has its own laws, as in Germany with the digital care law. At the European level, several steps have been taken since 2014 to ensure the security of users of activity trackers. In particular the General Data Protection Regulation (GDPR) which provids a solid framework for digital trust. The upcoming review of the GDPR may provide further useful elements in this regard. Other initiatives are the Regulation on the free flow of non-personal data (FFD), the Cybersecurity Act (CSA), and the Open Data Directive.

8. Conclusion

Wearable activity trackers are promising tools for optimizing health status. They can provide valuable data to motivate and educate the patient himself to increase physical activity level. However, patients' beliefs about physical activity and connected devices, and their ability to interpret and analyse the data provided should be addressed. Activity trackers can also help healthcare professionals in the assessment of disease flares, which is now possible with the use of machine learning. IA is also used to detect structural damage progression on images, to predict the response to biologic therapies or to perform faster literature reviews on rheumatic topics as exposed in this review.

The widespread use of these devices in epidemiological research raises technical challenges that must be understood by the research community. We believe that the next few years will see many developments in this field, to the ultimate benefit of the patient.

Author Contributions: Conceptualization: Thomas Davergne, Joanna Kedra and Laure Gossec; writing—original draft preparation: Thomas Davergne, Joanna Kedra and Laure Gossec.; writing—review and editing: Thomas Davergne, Joanna Kedra and Laure Gossec; visualization: Thomas Davergne, Joanna Kedra and Laure Gossec.; supervision: Thomas Davergne and Laure Gossec; project administration: Thomas Davergne. All authors have read and agreed to the published version of the manuscript.

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