Chapter

Artificial Intelligence in Musculoskeletal Conditions

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Abstract

Artificial intelligence (AI) refers to computer capabilities that resemble human intelligence. AI implies the ability to learn and perform tasks that have not been specifically programmed. Moreover, it is an iterative process involving the ability of computerized systems to capture information, transform it into knowledge, and process it to produce adaptive changes in the environment. A large labeled database is needed to train the AI system and generate a robust algorithm. Otherwise, the algorithm cannot be applied in a generalized way. AI can facilitate the interpretation and acquisition of radiological images. In addition, it can facilitate the detection of trauma injuries and assist in orthopedic and rehabilitative processes. The applications of AI in musculoskeletal conditions are promising and are likely to have a significant impact on the future management of these patients.

Keywords: artificial intelligence, musculoskeletal conditions, musculoskeletal radiology, skeletal trauma, physical and rehabilitation medicine, orthopedic surgery, sports medicine

1. Introduction

The term "artificial intelligence" (AI) was proposed by John McCarthy in 1956 [1]. It refers to computer capabilities that resemble human intelligence. It is a broad concept, involving both virtual (computing) and physical (robotics) elements [2], and this chapter is going to focus on the virtual aspects.

The term "AI" has been mistakenly used to refer to automated digital systems or probabilistic algorithms. It implies the ability to learn, for example, to perform tasks that have not been specifically programmed. An AI can analyze data and make decisions much like a person [3].

It is thought that AI could help change the mechanistic model of current medicine. Health being the result of a complex system based on multiple nonlinear interactions, it could help to better understand its functioning [4].

Nowadays, AI is deeply established in today's society. They are used in personal assistants (Alexa, Siri), music platforms to display recommendations (Spotify), or graphical applications (FaceApp). Although there are promising results, the application of AI in musculoskeletal medicine is just starting its way [5]. However, it is likely that AI will be part of our routine clinical practice in a few years.

2. Methodology

On 30 January 2023, a bibliographic search was carried out in PubMed and the Cochrane Library (Cochrane Reviews) using "artificial intelligence musculoskeletal" as keywords. We found 957 articles in PubMed and 18 in the Cochrane Library (of which 10 were repeated in PubMed). In other words, we used a total of 965 article abstracts, of which we finally analyzed 51 because we subjectively considered them to be the best and most closely related to the chapter title. The remaining 914 articles were excluded (**Figure 1**). This way of including and excluding articles and the fact that we did not use other bibliographic search engines (Web of Science, Google Scholar, and Embase) can be considered as two limitations of this chapter, as some important publications were probably not included in it. In addition, due to the novelty of the topic studied, we have included one book and three websites because of their relevance and the topicality of their content. However, we would like to mention that the bibliographical references are so abundant (thousands) that one way or another, there could always be something important left out, even if a systematic review and meta-analysis is carried out.

3. Types of AI

An AI is an iterative process involving the ability of computerized systems to capture information, transform it into knowledge, and process it to produce adaptive

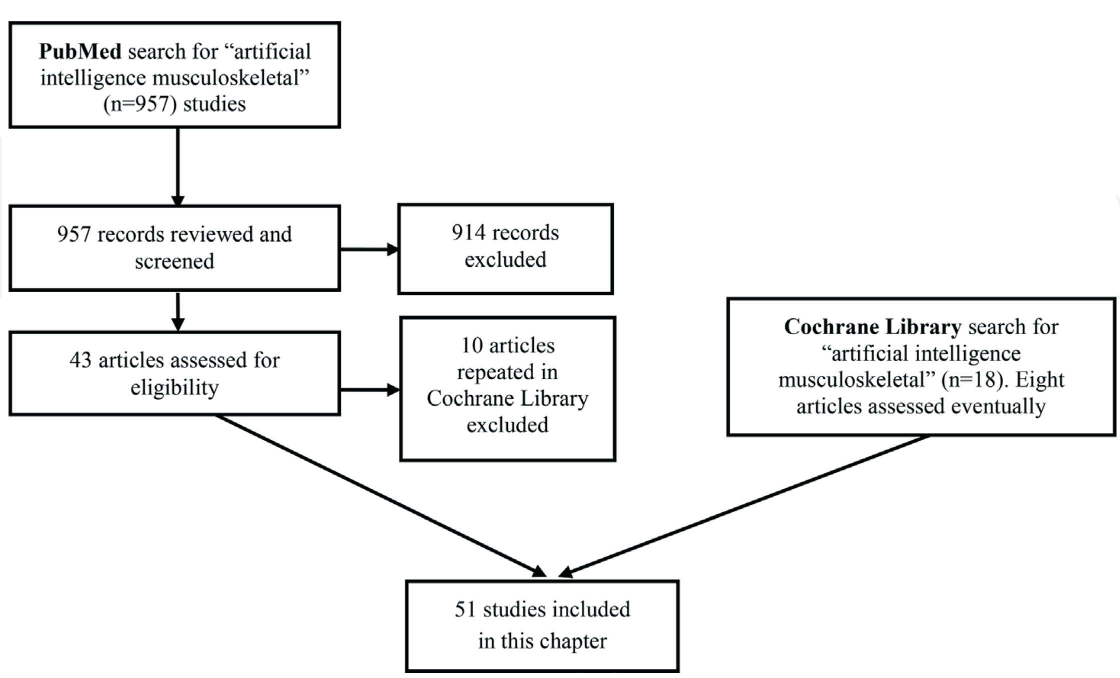

Figure 1.
Flow chart of our search strategy regarding artificial intelligence (AI) in musculoskeletal conditions.

changes in the environment. AI is capable of surpassing the speed of human analysis in many cases. Within this broad framework, there are different systems with their own characteristics.

Machine learning (ML) is a branch of artificial intelligence that refers to systems and algorithms capable of learning and improving through data analysis. Unsupervised ML does not require a labeled database to perform its training. Instead, it can identify nonapparent or hidden relationships in different data patterns. Supervised ML requires a labeled database in order to perform training. This database contains information in which the input and output are linked. This is what the computer uses to perform the correct matching.

Deep Learning (DL) is a type of ML capable of learning complex tasks through the analysis of large amounts of information with which it is trained [6]. An artificial neural network composed of nodes arranged in a hierarchy of levels is used in the DL. The network is able to process basic information at the initial level and forward it to the next level. There it is integrated with data from other nodes and passed to the next level. This process is done iteratively until the system learns the task, such as identifying a particular pattern. For example, DL techniques can be applied to radiologic studies to develop computer algorithms capable of analyzing images, classifying, and segmenting them [7].

Convolutional neural networks (CNN) are a subtype of DL especially used in image processing. They use learnable layers and filters through which data are passed and processed in a complex way, until they are completely transformed to the final layer or output layer. CNNs take advantage of the position of pixels in the images to reduce the processing complexity and parameter requirements per layer.

One of the great advantages of DL and CNN is their ability to be trained end-to-end. This means that the training model only needs input data, for example, knee magnetic resonance imaging (MRI) and a set of gold standard labels, medial meniscal lesion, and no medial meniscal lesion. The algorithm is capable of self-learning, considering by itself which elements are most relevant to perform a process. Since training a CNN is an iterative process, a larger volume of information usually yields better performance of the algorithm. In addition, although the computational power required to train DL algorithms is high, subsequent analysis of new data is faster and easier than in other AI systems.

4. How to generate AI in musculoskeletal medicine?

To generate an AI, a large volume of labeled data are needed to train the AI system and generate a robust algorithm. Otherwise, the algorithm can only be applied in a limited way. In the case of radiology, 49% of the papers using DL use databases of 101 to 1000 cases, 25% less than 100 cases, and only 6% use more than 10,000 cases [7]. It seems necessary that centers could coordinate to increase the size of their databases. In this regard, there are de-identified public databases that can be used to train AI algorithms, such as musculoskeletal radiographs (MURA), with almost 41,000 images of the upper extremity labeled as fracture or nonfracture by radiologists [8].

Many times, images processed by AI systems are manually selected, which is very time-consuming. It is vital that the database that is going to train the AI is appropriate to what is to be analyzed and has no flaws. In addition, it is recommended for the data to be homogeneous and of a volume proportional to the complexity of the computational task.

Unsupervised learning is likely to be critical in the future for building new AI systems. However, most successful AIs currently use supervised learning that may actually hinder their development [9].

One element used in some algorithms is heat maps in DL systems. Their use allows us to find out the part of the image that contributes the most within the analysis and reduce the impact of incorrect data. For example, if the heat map points out that a part of the image is being analyzed while the lesion is in a different one, it can be discovered that the algorithm is not processing the correct data.

5. Applications of AI in musculoskeletal medicine

5.1 Application in image interpretation

Errors in image interpretation in trauma radiology can increase morbidity and mortality, and it has been estimated that there can be up to a 4% error rate even by a trained radiologist [10]. There is an increasing pressure on physicians to interpret radiological images due to their growing use. It has been estimated that the greatest number of undiagnosed fractures occur in patients assessed between 8:00 p.m. and 2:00 a.m. This is probably because physicians who can assess these images may not be available in certain facilities or at certain times of the day [11].

The application of an AI in the world of radiology is the natural consequence of history and discipline, which has been characterized by incorporating technological innovation into clinical practice [12]. However, most existing algorithms used to identify fractures usually provide performance similar to, but not superior to, the capabilities of an expert radiologist. Therefore, it is possible that physicians who are not specialists in musculoskeletal radiology may benefit the most from using these AI tools. For example, CNNs have been used to detect fractures on radiographs in different anatomic locations, including the upper extremity, lower extremity, hip, and spine [13].

On the other hand, AI-based imaging systems are usually used in specific anatomical locations, so they should be integrated with each other to have an impact on clinical practice. An example of this would be a study in which 715,343 radiographs from 16 anatomical sites and 10 CNNs were used to detect fractures with promising results [14]. Another example would be the use of DL on computed tomography (CT) images to detect osteoporotic femoral neck, calcaneal, and vertebral fractures with an acceptable result [15]. An interesting aspect is the ability of the AI to detect fractures that are inconspicuous to the human eye. An algorithm with the ability to detect subtle lesions might not be able to discover radiographically obvious fractures [16].

Algorithms have also been used to detect anterior cruciate ligament tears, finding no difference in sensitivity or specificity versus expert radiologists [17]. AI has also shown good results for diagnosing meniscal tears [18]. DL has also been used to evaluate acute and chronic cartilage lesions [19].

5.2 Application in orthopedic surgery and orthopedic trauma

The incorporation of AI to assist in the surgical procedure has aroused great interest at present. For example, AI has been used as an assistant for image segmentation. The algorithm is able to differentiate the image fragment that is a healthy tissue from the mass to be studied or removed. This facilitates a time-consuming task in a fast and automated way [20].

AI has also been used in algorithms for predicting outcomes or costs associated with the surgical procedure. The DL is able to process a large amount of input data (age, comorbidities, and gender) and generate a certain outcome with predictive capacity (cost of hospitalization). For example, one paper analyzed 175,042 patients undergoing primary total knee replacement surgery with 15 preoperative variables, being able to estimate length of hospital stay and hospital costs, adjusting certain comorbidities [21].

Furthermore, AI has been used to help decide on the appropriateness of performing a surgical intervention, for example, to preoperatively assess the risk of death or complication. This would serve to provide the surgeon and patient with better information when deciding on the optimal management option [22].

5.3 Clinical workflow

In general, AI systems have the potential to assist physicians in certain tasks by improving the ability to diagnose and treat accurately despite the increased workload. Within the radiological practice, AI could improve two very important aspects such as effectiveness and efficiency. Effectiveness implies accuracy in interpreting radiological images and taking optimal clinical action. On the other hand, efficiency implies the optimization of workflows to make the best use of available resources and avoid clinical errors. These benefits would be achieved even considering the increased care pressure on physicians nowadays and the enormous workload involved in imaging on modern musculoskeletal radiology machines [12].

AI can be used to optimize clinical workflow and prioritize the tasks to be performed by clinicians. For example, an algorithm would be able to analyze a queue of images pending assessment and determine those that should be reviewed earlier because they are more likely to be pathological. This could be a critical advance in emergency situations, such as reviewing brain scan images to rule out intracranial hemorrhage [23].

Furthermore, it could accelerate image acquisition. Algorithms have been used to obtain MRI scans in five minutes that have higher image quality than other conventional MRI scans and can be optimally assessed by specialist radiologists [24].

5.4 Clinical decision-making

AI has been used as a decision support tool [25]. For example, in the field of rehabilitation, a DL algorithm has been developed to recommend to patients with low back pain, and according to clinical aspects whether they should go to their primary care physician, a physical therapist, or whether they can perform self-management [26].

DL has also been used to develop pain phenotypes based on resonance imaging findings. However, due to the complexity of pain, the role of this classification in daily care is unclear [27].

One aspect that AI could enhance would be biomarkers. In many cases, certain biomarkers cannot be used because they are too costly to obtain in terms of time or money. For example, in frailty, DL has been used to analyze body composition (bone mass, muscle mass, and fat distribution) in a CT slice at third lumbar vertebra (L3) to assess frailty and sarcopenia [28]. This would allow obtaining important data that would allow prescribing rehabilitation programs more appropriately.

AI has also been used to classify fractures. There are algorithms that have shown 72% accuracy in calcaneal fracture classification using CT [29], with similar or superior effectiveness to orthopedic surgeons for classification of proximal humerus fractures [30], good performance in hip fractures [31], femur [32], and ankle [33].

AI systems that combine clinical data in rib fractures with imaging test results have been published to improve sensitivity and reduce diagnostic time compared with expert radiologists [34].

DL has also been used to discover hidden fractures by combining clinical and radiological data. For example, an algorithm could predict the likelihood of posterior malleolar fracture in patients with tibial shaft fractures by analyzing the image along with other clinical, demographic, and injury data of the patient such as age, mechanism of injury, and fracture type [35].

5.5 Prediction and risk of musculoskeletal injuries

A growing field for the use of AI is sports medicine, although not only for the purpose of predicting whether an athlete is going to suffer an injury during a match or training but also about measuring the risk of injury to the athlete by analyzing all intrinsic and extrinsic factors and their relationship to each other, since injuries occur because of these. For example, in basketball, extrinsic factors could include the ball, the type of floor, the playing field, the temperature, or the time at which the game is played. Within intrinsic factors, we would have previous injuries, age, or gender [36].

In addition to the sport, the predictive factors are probably related to biological variables of the athletes, although no clear relationship has been established. Static traits such as flexibility, strength, or balance have usually been considered to predict injury. However, the dynamic and changing aspect of these characteristics, as well as their mutual influence, have not been taken into account [37]. AI could help manage this data.

5.6 Application to improve health literacy

Literacy is a heterogeneous and multidimensional concept that implies the ability to understand, evaluate, use, and interact with written texts in order to participate in society, achieve one's goals and develop one's potential. Health literacy involves the ability to enable individuals to obtain, understand, appreciate, and use information to make decisions and take actions that have a significant impact on their health status [38].

To improve health literacy, one tool that could be used within AI would be the use of chatbots. A chatbot is a computer system that mimics a human conversation by text or voice. Despite its potential, users of these systems often abandon them after the first or second encounter with it [39]. AI has been incorporated to achieve more empathetic and human interfaces that more realistically simulate user interaction [40].

Chatbots could facilitate health literacy, improve disease self-management, stimulate treatment adherence, or improve administrative services, such as medical appointment management [41].

These systems are also used to facilitate adherence to a home rehabilitation exercise program at hospital discharge. The role of algorithms here would be to enhance exercise adherence, achieving improved patient motivation and involvement [42]. In addition, AI could solve the fact that resources to assist patients in home-based Rehabilitation are often generic and not well adapted to individual needs and preferences [43]. For that reason, AI has been used to improve the performance of home exercise programs [44].

5.7 Data management and wearable devices

A fundamental aspect of data management today is big data. Big data involves a set of tools that analyzes data too large or too complex to be processed by traditional statistical systems. This complexity has led to the use of AI systems to analyze Big Data. For example, it has been successfully employed to coordinate the results of massive multicenter studies in the field of drug discovery [45].

In the field of musculoskeletal diseases, a large volume of data are being recorded through imaging, electronic medical records, sensors in wearable devices, and in genome sequencing. Major advances are also being made in analysis and processing systems. Thus, analyzing in detail the multidimensional information in a patient's electronic health record would provide a powerful tool to facilitate individualized health management [46].

Fuzzy logic-based AI systems that are capable of analyzing questionable, incomplete, or inconsistent clinical information have been employed and still facilitate the diagnostic management of certain pathologies [47].

Wearable devices are ubiquitous today. These devices are equipped with different sensors (accelerometers, global positioning system, gyroscopes. ..) that can record a large number of biological parameters and also have permanent connectivity. Internet of Things (IoT) refers to the set of physical objects with sensors and programs connected to other devices and systems through a network. One of the practical applications of this type of technology would be to extract a high volume of data from lifestyles, training, and sport events [48]. AI could use all this data and integrate it with other sources of information to generate algorithms to make clinical decisions or predict adverse events.

In addition to sports activity, wearables are used by users to record sleep quality, general physical activity, and walking (speed, distance traveled, and number of steps). However, it has not yet been possible to leverage this information to optimize healthcare or decrease healthcare costs [49]. It is thought that AI may be the solution to harness the performance of all this data and improve patient health.

5.8 Bioethics

By facilitating the acquisition and analysis of images, AI could improve equity in healthcare. This would facilitate access to optimal radiological assessments in areas where specialists are not available such as developing countries or rural areas [50].

It has been proposed to use AI-based systems to facilitate the entry of clinical information to reduce the time and cognitive load required to perform such a task. However, from an ethical and human point of view, there are controversies, since the doctor–patient relationship is based on trust and close treatment, and these are not assumable by a computer [51]. Clinical care remains a human process. It should never be reduced to applying more or less complex diagnostic or treatment algorithms. A patient's health should not be limited to a mere statistical concept [52]. It seems unreasonable and unethical to make clinical decisions based solely on computerized processes.

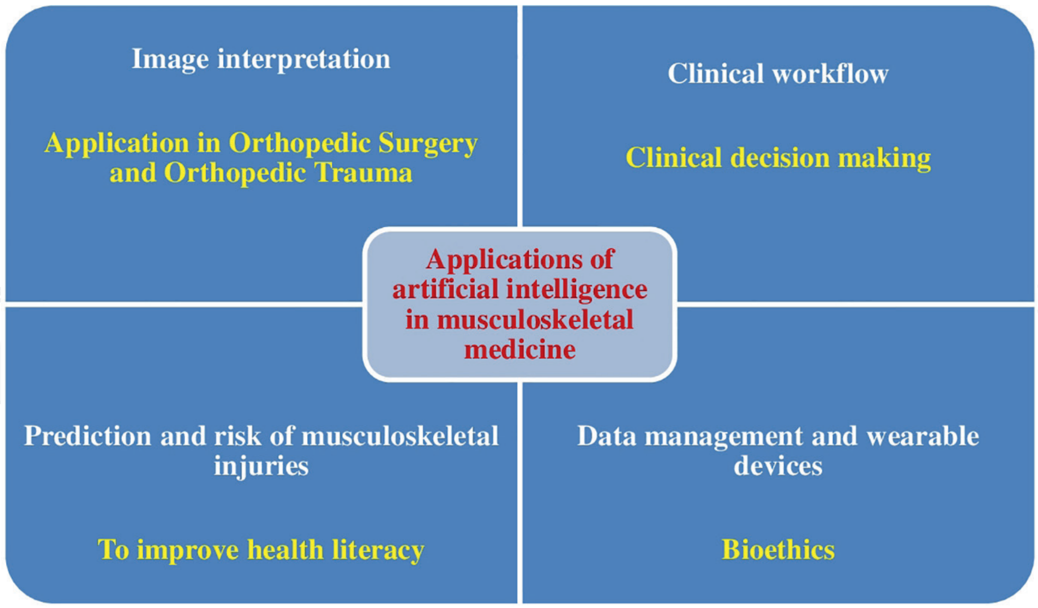

Figure 2.
Current applications of artificial intelligence (AI) in musculoskeletal medicine.

Another aspect of ethical interest is related to the costs associated with surgical procedures in which the use of algorithms to adjust the payment models per procedure has been evaluated. Although the price of interventions is usually fixed, patient comorbidities are known to increase the number of perioperative complications and produce worse outcomes [53]. This could result in some centers selecting lower-risk patients to extract a higher financial return, creating an ethical issue that must be resolved before recommending widespread use of these algorithms [54].

When interpreting radiological evidence, the physician not only classifies and analyzes the images but also interprets them within a broad clinical context. This clinical reasoning ability is acquired through the clinician's professional experience and even during the undergraduate years [55]. In fact, not all clinical decisions are made based on objective aspects. Sometimes, an experienced clinician may make clinical decisions based on experience or intuition. Even the clinician cannot explain why he or she makes this decision, and yet, in many instances, these decisions are accurate. An AI, devoid of feelings and emotions, can hardly make up for this aspect [52]. It is controversial to think what will happen in the case where an algorithm recommends one course of action and the clinician thinks that another clinical action should be taken.

On the other hand, clinical decision-making based on the use of AI algorithms, and the possible errors in diagnosis and treatment that this may cause, implies an important liability issue. And it is not clear who should assume this responsibility: the clinician, the health center or the company that has designed the algorithm. **Figure 2** summarizes current applications of AI in musculoskeletal medicine.

6. Limitations of artificial intelligence

AI is far from being able to solve all the problems that exist in musculoskeletal disease management today. To train AI systems, large, appropriately labeled databases are needed, which are expensive to build. In addition, if there are many correlated variables, AI can establish false correlations.

In radiological image interpretation, two parameters must be taken into account: accuracy and recall. An algorithm that has a high recall will classify all images with lesions as positive, but will have a low accuracy. However, an algorithm that only classifies a lesion when it is completely certain will have high accuracy but low recall. There is still great difficulty in achieving AI systems that are effective in both capabilities, so algorithms should be used depending on the clinical task to be performed: confirmation or screening [18].

On the other hand, many algorithms can only be applied in common pathologies. This makes them not applicable across the board. In addition, different AI systems may analyze the same data differently.

7. Conclusions

AI is an emerging reality that could produce a paradigm shift in the management of musculoskeletal diseases, from mechanistic to predictive medicine. The different algorithms may also facilitate the acquisition and interpretation of radiological images, provide information related to surgical processes, facilitate the decision-making process by clinicians, or enhance patient health education. However, they still have many limitations and raise important ethical issues. An algorithm cannot replace the role of clinicians, as they must bring their knowledge, experiences, skill, and humanity to patient care. Finally, AI systems must be integrated sensibly and moderately within care processes.

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