[Frontiers in Bioscience-Landmark, 26(11), 1340-1348, DOI:10.52586/5027] https://www.fbscience.com

Review

Artificial intelligence in musculoskeletal conditions

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1. Abstract

Artificial intelligence (AI) is an iterative process by which information is captured, transformed into knowledge and processed to produce adaptive changes in the environment. AI is a broad concept, involving virtual (computing) and physical (robotics) elements. In this narrative literature review, we focus on the aspects of AI that present major opportunities for developing health care. Within a few years, AI will be part of our daily clinical practice. Although significant advances are being made, the application of AI in musculoskeletal medicine is still in its early stages compared with its implementation in other areas of medicine. AI is increasingly being employed in fields such as musculoskeletal radiology, skeletal trauma, orthopedic surgery, physical and rehabilitation medicine and sports medicine, as well as for "big data" and AI in gastrointestinal (GI) endoscopy related injuries. Among the limitations of IA are that it analyzes information based on the data it is supplied, which must therefore be well-labeled and that some algorithms such as DL uses more time, data, and computational power than other techniques. Moreover, AI currently does not solve the problem of causality that exists in medicine with observational data; information that physicians interpret within a broad clinical context. AI should therefore be integrated in a prudent and reasonable manner into the workflows of health professionals.

Submitted: 5 August 2021 Revised: 23 September 2021 Accepted: 22 October 2021 Published: 30 November 2021

2. Introduction

Physiological processes function as a complex system based on numerous nonlinear interactions between its components. Each complex system is different, and finding general rules is difficult [1].

Artificial intelligence (AI) could help better understand how these health-related systems work. AI is an iterative process by which information is captured and transformed into knowledge, which is then used to modify the environment. It is a broad concept, involving both virtual (computing) and physical (robotics) elements [2]. This article will focus on the virtual aspects.

AI is widely present in today's society in the form of personal assistants (Alexa, Siri), video-on-demand platforms that display recommendations (Netflix), image and video processing applications (FaceApp) and self-driving vehicles (Tesla) [2].

There are major opportunities for implementing AI in health care. Within a few years, AI is likely to change the way daily clinical practice is conducted [3].

Although major advances are being made, the application of AI in musculoskeletal medicine is still in its early stages compared with its implementation in other areas of medicine [4].

3. What is artificial intelligence?

The term AI was proposed by John McCarthy in 1956 [5] and refers to the capabilities and processes performed by computers that resemble human intelligence. However, the term has been misused to refer to probability systems or automated computerized processes. AI (Fig. 1) implies a capacity for learning, i.e., being able to perform tasks that have not been specifically programmed. An AI system must be able to analyze information and make decisions in a manner similar to humans [6].

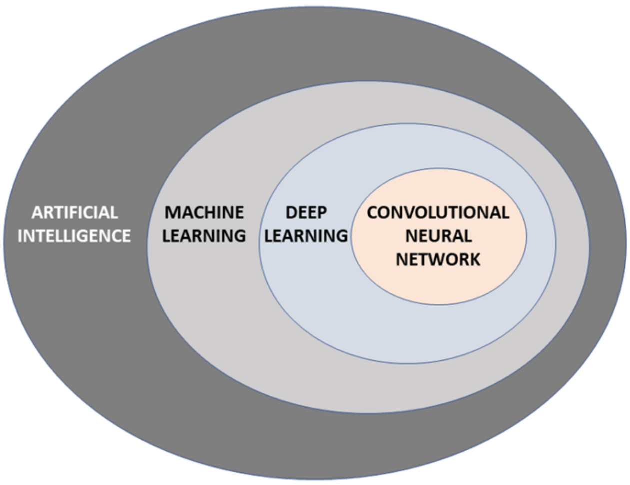

Fig. 1. Various artificial intelligence (AI) systems.

Machine learning (ML) is a branch of artificial intelligence that uses various systems and algorithms to learn and refine its operation through the use of data. ML can be supervised or unsupervised (Table 1). To perform the training, supervised ML (Figs. 2,3) requires a labeled database that contains information with a set of features that are linked to a set of results (output), which the system uses to learn the appropriate correspondence. Unsupervised ML (Fig. 4) does not require a labeled database for training but instead is able to identify non-apparent relationships or hidden patterns among varying data [7].

Deep learning (DL) is a type of ML capable of learning complex tasks through the use of large volumes of training information [8]. DL systems need a large training database to achieve adequate performance. Most published papers have trained their DL algorithms using between 101 and 1000 cases [9]. DL uses an artificial neural network composed of neurons (nodes through which data flow) arranged in a hierarchy of levels. The network can process basic information at the initial level and forward it to the next level, where it is integrated with data from other neurons and passed to the following level. This process is performed iteratively until the system learns the task, such as identifying a particular pattern. DL techniques can be applied to, for example, radiological studies to develop computer algorithms capable of analyzing, classifying and segmenting images [9].

Convolutional neural networks (CNNs) are a subtype of DL that is especially useful in image processing. CNNs use a series of layers and learnable filters through which data are passed and processed in a complex manner, until a result is obtained in the final layer or output layer. CNNs take advantage of the pixel location in images to reduce the computational processing complexity and parameter requirements per layer when compared with the conventional artificial neural network used in DL [10].

One of the major advantages of DL and CNNs is their ability to learn independently which features in the input data lead to the desired results, once the output data have been labeled (e.g., radiological images of bones with and without fractures. Given that CNNs training is iterative, there is a trade-off between database size and algorithm performance. Using a DL algorithm to analyze new data requires less time and computational power than other AI techniques [3].

4. Creating an artificial intelligence system

A large database of labeled data is needed to train an AI system and generate a robust algorithm. If the data are unlabeled or insufficient, then the algorithm will be unable to process new data and will be unsuitable for use in other areas. One of the problems with DL systems is that they are often developed in an uncoordinated manner in different centers with small databases. The vast majority of studies

Table 1. Differences between supervised and unsupervised machine learning (ML).

	Supervised	Unsupervised
Data entered	Tagged	Unlabeled
Learning capacity	Yes	Yes
Requires human intervention	For entering, sorting and labeling data	For data entry only
Output data	Expected according to previous classification	Unexpected relationships
Utility	Performing scheduled task	Finding hidden patterns

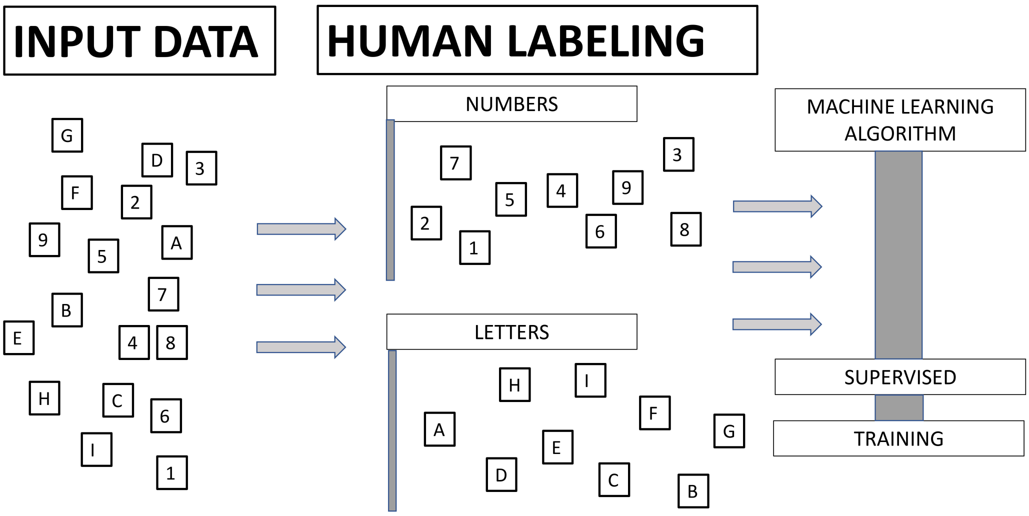

Fig. 2. Algorithm training (supervised machine learning [ML]). The input data are manually labeled by a human. These labeled data are subsequently processed by the algorithm, which learns the appropriate functions to perform the correct classification and is thereby trained.

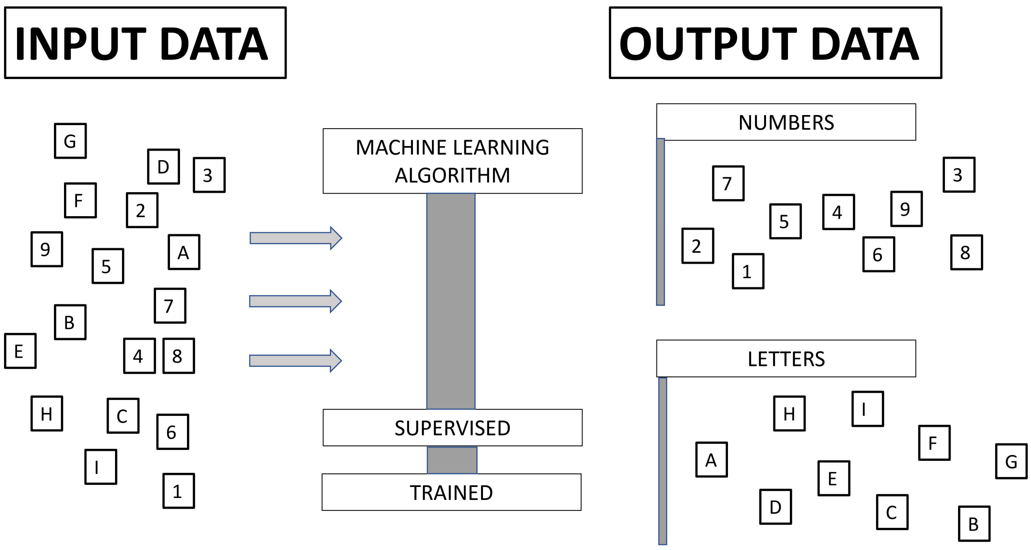

Fig. 3. Application of the algorithm (supervised machine learning [ML]). The input data are analyzed by the trained algorithm, which can classify the data according to the labels provided by the human.

using DL have employed databases with fewer than 10,000 cases [9].

Most AI systems require that the images for analysis be selected by humans, a selection process that has to be performed manually and can be time-consuming. When creating databases to train AI, it is essential that the data be correctly labeled and that a sufficient volume of data is available. To avoid errors, it is worth considering the variability that might exist between various centers and technical teams [11].

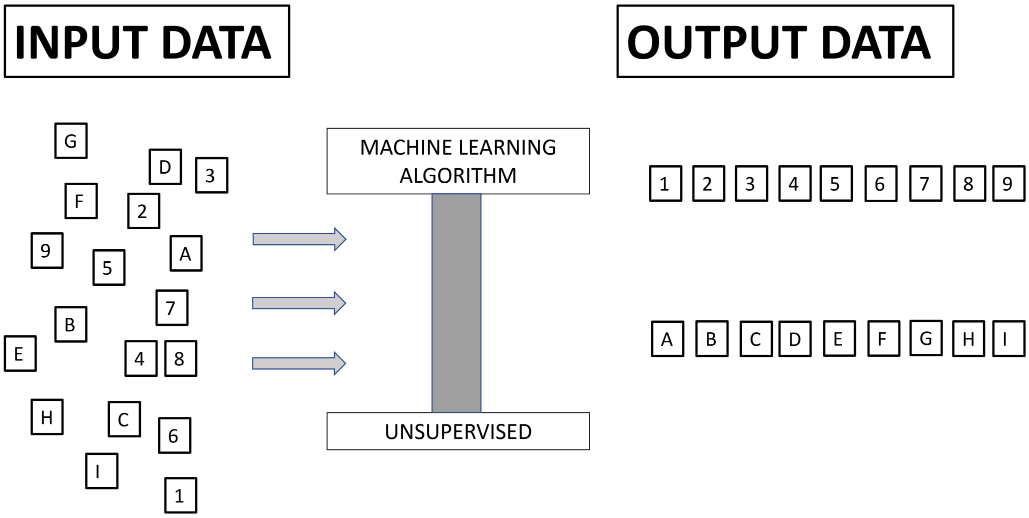

Fig. 4. Application of the algorithm (unsupervised machine learning [ML]). The unsupervised algorithm analyzes the input information and establishes initial non-apparent relationship patterns.

Table 2. Aspects that artificial intelligence (AI) could bring to radiology.

Designing imaging protocols and individualized protocols for each patient
Reducing image acquisition and processing time
Automatic image correction for images with noise or poor image quality
Automatic identification of features within images
Automated diagnostic input
Radiological pattern recognition and integration with other sources of information

Most AIs with more practical and successful applications use supervised learning, which limits their development possibilities to a certain extent. However, unsupervised learning is considered essential for building future AI systems [12].

De-identified public databases can be used to train AI systems, such as the musculoskeletal radiographs database, which contains approximately 41,000 images of upper extremities labeled as fractured or non-fractured by expert radiologists [13].

5. Application in musculoskeletal radiology

One of the characteristics of the radiology field is its incorporation of technological advances into clinical practice. Throughout the history of radiology, there have been several paradigm shifts. Computed tomography (CT) started a revolution in the diagnosis of brain conditions. Another fundamental advance was the advent of magnetic resonance imaging (MRI) [14]. AI will likely be the next paradigm shift. The potential contributions of AI to radiology are shown in Table 2 [15].

AI can improve efficiency by optimizing workflows in image interpretation and can reduce the imaging workload, which is especially important in modern scanning and MRI techniques that require dozens of sequences for analysis. AI could also improve clinical decision making, increasing the accuracy in interpreting clinical images. These advantages could reduce the risk of error [15].

The application of AI in ultrasonography could improve healthcare equity in developing countries and rural areas due to its benefits [16] in detection [17], diagnosis [18] and segmentation [19] (Table 3).

To analyze how a DL system works in image processing, heat map analyses can be useful. The technique identifies the part of the image that requires the largest processing load and can help to better understand whether the algorithm is using incorrect data. For example, to assess an algorithm's ability to detect fractures, a heat map can indicate whether a portion of the image far from the fracture is being analyzed, thereby indicating that the algorithm is processing incorrect data [20].

From a clinical perspective, AI has been used to detect anterior cruciate ligament ruptures, with no differences in sensitivity or specificity compared with analyses by expert radiologists [21]. AI has shown good results in diagnosing meniscal tears [22]. DL has also been employed to assess acute and chronic cartilaginous lesions [23].

AI can be used to improve clinical workflows and prioritize the tasks to be performed by clinicians. For example, AI can be used to analyze a large number of images awaiting review, prioritizing the study of those images that

Table 3. **Benefits of applying artificial intelligence (AI) in ultrasound diagnostic imaging.**

Detection: Automatic identification of normal or pathological anatomical structures	
Diagnostics: Ultrasound image processing to detect pathological findings	
Segmentation: Automatic delineation of the boundaries of specific anatomical areas	

are most likely to show lesions/injuries, which can have important implications, such as the detection of intracranial hemorrhaging in brain scan images [24].

AI can also be used to accelerate image acquisition. AI systems have been employed to obtain rapid MRI scans (within 5 min compared with 15 min for regular scans), which can be interpreted in a similar manner to conventional MRI scans and are even considered of higher quality by clinicians who review the images [25].

AI has been used as an assistant for automated image segmentation, which enables the extraction of useful biomarkers to facilitate the diagnosis. AI algorithms can differentiate the part of the image that corresponds to the mass to be studied/removed and the part that constitutes healthy tissue, allowing this time-consuming task to be performed quickly and automatically [26].

6. Application in skeletal trauma

Extremity trauma is one of the main reasons for emergency department visits and requires high healthcare expenditures [27]. Managing trauma patients almost always involves diagnostic imaging, which can range from radiographs and ultrasound to MRI.

Errors in interpreting trauma imaging result in increased morbidity and mortality. It has been estimated that the error rate is as high as 30%, even with imaging specialists [28]. Due to the increased use of imaging, there is increasing pressure on physicians to interpret these images. Physicians who can interpret these images might not always be available in certain facilities or at certain times, resulting in a risk to patients. It has been estimated that there is a peak of undiagnosed fractures between 8:00 PM and 2:00 AM, probably due to the unavailability of radiologists [29].

CNNs have been used to detect fractures in radiographs at various anatomical locations, including the extremities, pelvis and spine [30]. Most CNNs systems are developed for specific locations, although there are ongoing efforts to integrate several such algorithms [31]. The published algorithms for identifying fractures have shown a performance that has not exceeded the capabilities of a musculoskeletal specialist. The use of these AI tools should therefore be limited to specific clinical tasks [32]. Physicians who are not musculoskeletal radiology specialists would benefit the most from these AI tools.

AI has also been used to classify fractures. There are algorithms that have shown a hip fracture classification accuracy of 93.7% [20], a femur fracture classification accuracy of 86% [33], a proximal humerus fracture classification accuracy of 65–86% [34] and good performance in classifying fractures around the knees [35] and ankles [36].

AI has been used to detect fragility fractures, such as osteoporotic fractures, in plain radiographs with an accuracy of 86% [37]. CNNs have also been used to detect osteoporotic fractures through MRI with an accuracy of up to 88% [38].

DL has been used to detect occult fractures. For example, a model has been developed that can detect scaphoid fractures that go undetected by human specialists. However, the system capable of detecting previously undetectable fractures missed radiographically obvious fractures [39]. Algorithms combining clinical and radiological data have also been designed. Algorithms have been developed that combine the results of image test analyses with clinical data on rib fractures, which, compared with expert radiologists, could improve the sensitivity and reduce the diagnostic time by a couple of minutes, while maintaining similar accuracy [40].

7. Application in orthopedic surgery

In orthopedic surgery, the success of an intervention does not only imply anatomical restoration for the injury or improvements in parameters such as mobility and strength. As important, if not more so, is the subjective result perceived by the patient. Efforts have therefore been made in recent years to collect patient-reported outcome data [41]. AI could help integrate these subjective data with other measures to perform an overall assessment and predict intervention outcomes.

The advantage of AI techniques such as DL is that they can process large amounts of input data (patient age, comorbidities, and sports activity) and generate a single outcome variable with predictive capacity (e.g., cost of hospital stay). AI has been used to help decide whether to perform surgery and to preoperatively estimate the risk of mortality and postoperative complications, thereby furnishing surgeons and patients with more accurate data for making better decisions [42] and providing better informed consent. A study from Kamuta *et al*. [43] employed artificial neural networks to analyze data from 111,147 patients who underwent total shoulder prosthesis and reverse shoulder prosthesis to predict length of stay, discharge status and inpatient costs, showing good accuracy and reliability.

The use of AI has also been proposed for adjusting pay-per-intervention models, which usually employ fixed fees in which each intervention has a unique cost. However, patient comorbidities can increase the number of perioperative complications and lead to poorer outcomes [44], which, in some centers, can result in the selecting of patients with lower risk to obtain a higher economic return, which creates ethical problems [45].

8. Application in physical and rehabilitation medicine

The use of AI in the brain-computer interface has been studied for some time in the fields of physical and rehabilitation medicine [46] and neuroprosthetics [47]. AI applied to the virtual realm is also being used for rehabilitation [47].

Patients must often continue rehabilitation exercises at home after being discharged. To improve compliance with these exercise programs, patient motivation and involvement need to be strengthened [48]. Resources to assist patients in home rehabilitation are often generic and not well adapted to the individual's needs and preferences [49]. AI has therefore been used to improve the delivery of home exercise programs [50].

DL has been used to develop pain phenotypes based on resonance imaging results. Due to the complexity of pain, however, the utility in clinical practice of this classification is unclear [51].

AI has also been used in rehabilitation as a decision-making support tool [52]. For example, a DL algorithm has been developed to recommend, based on certain criteria, whether patients with low back pain should perform self-management and whether they should see their primary care physician or therapist [53].

AI could also be used in the field of biomarkers. Certain biomarkers cannot be regularly used because they are too expensive to obtain, due to the time required to extract them. In the case of frailty, for example, DL has been employed to analyze body composition (bone mass, muscle and fat distribution) in a CT slice at the L3 level to detect frailty and sarcopenia [54], thereby obtaining relevant data for planning a more appropriate rehabilitation program.

9. Application in sports medicine

In sports medicine, AI can measure the risk of injury to athletes by analyzing the factors involving the athletes and their environment, as well as their relationship. Injuries can occur as a consequence of these factors. For example, to assess the risk of injury in soccer, the characteristics of the ball, playing field and its environment should be included, while the athlete's factors include age, sex and previous injuries [55].

These predictive factors are likely related to biological variables, although a definitive relationship has not been established. A series of static characteristics, such as flexibility, strength and balance, have classically been considered as predictors of injury events. However, internal variations of these characteristics and their relationships with each other have not been taken into account [56]. AI could help manage these data.

Another interesting aspect is the development of new technologies that allow high-quality data to be extracted from training and sporting events [57]. There is a large number of wearable devices capable of providing an immense amount of biomedical data; AI can use these data and integrate them with other sources of information to generate algorithms for planning training and matching loads.

10. Other uses

10.1 Big data

An immense volume of data is currently being recorded through images, electronic medical records and sensors in portable devices. Major advances are also being made in measurement, analysis and processing systems. The clinical information in the patient's history could be the information needed to make personalized predictions regarding the patient's health [58].

Big data refers to a set of tools that analyze a data set that is too large or complex to be processed by classical statistical systems. This complexity has led to the use of AI systems to analyze big data (e.g., in the field of drug discovery to coordinate the results of massive studies performed across multiple centers) [59].

Fuzzy logic-based AI systems have been employed to analyze questionable, incomplete and inconsistent clinical information and facilitate the diagnosis of certain conditions [60].

10.2 AI in gastrointestinal (GI) endoscopy related injuries

The increasing number of GI endoscopies being performed worldwide has raised concerns about the health of the endoscopists who must perform these techniques. It has been reported that 39-89% of endoscopists suffer work-related musculoskeletal injuries, mainly at the level of the hands, spine and shoulders, requiring surgery in up to 64% of cases. The application of IA during endoscopy could be a way of facilitating the performance of the technique or obtaining the results, reducing the physical effort required and improving ergonomics [61].

11. Limitations of artificial intelligence

AI analyzes the information based on the supplied data but does not solve the problem of causality that exists in medicine in observational data. If there are multiple correlated variables, AI might establish false correlations [2].

Large databases with appropriately labeled information are needed to train DL systems. In the case of radiological evidence, images with unambiguously identified conditions (ideally with histopathological and surgical confirmation) are needed; however, these databases are expensive to build. As with interobserver variation, different AI systems might interpret the data differently. Numerous published algorithms also do not have open source code that can be publicly reviewed. Due to their “black box” nature, these algorithms are complicated to analyze, and their performance is difficult to compare [62].

Most of the algorithms under development produce binary results (e.g., presence or absence of injury). Moreover, most of them focus on common conditions, which makes them inapplicable for many clinical situations [3].

In the case of imaging tests, two parameters need be considered: precision and recall. An algorithm that has high recall will classify all images with an injury as positive but will have low accuracy. However, an algorithm that only classifies an injury when it is completely certain will have high accuracy but low recall. The goal is to achieve an algorithm that performs well on both parameters. However, sometimes it is desirable to use different IA systems depending on the intended task (screening or confirmation) [22].

Despite the undeniable improvements in medicine due to the technological advances in AI, clinical care remains a human process and should never be reduced to applying more or less complex diagnostic or treatment algorithms. A patient’s health is not a mere statistical concept [63]. Making clinical decisions based solely on computerized processes does not seem reasonable or ethical.

When interpreting radiological tests, physicians not only classify and analyze the images but also interpret the images within a broad clinical context. This clinical reasoning is acquired through professional experience and throughout their training [64]. Not all clinical decisions are made on the basis of objective data or knowledge. Occasionally, an experienced physician might make clinical decisions based on intuition. An AI that is devoid of intuition can hardly make up for this deficiency [63].

Clinical decision making based on the use of AI algorithms and the possible diagnostic and treatment errors that this might cause entail a significant liability problem. The long-term implications of the use of AI systems on patient health are uncertain [65].

12. Conclusions

AI is an emerging reality that can produce a paradigm shift in musculoskeletal health, from descriptive to predictive medicine. Various AI systems can facilitate clinical care for professionals, improving the diagnosis and treatment in numerous processes. However, AI systems still have many limitations and raise operational and ethical issues. In any case, clinical decisions should not be made exclusively by applying an algorithm. Rather, AI systems should be integrated prudently and reasonably within the practitioner’s workflow.

13. Author contributions

JMR-B, HDLC-R, ECR-M—Conducted the literature search and planned the review. JMR-B wrote the first draft of the manuscript. All the authors have read and agreed to the published version of the manuscript.

14. Ethics approval and consent to participate

Not applicable.

15. Acknowledgment

Not applicable.

16. Funding

This research received no external funding.

17. Conflict of interest

The authors declare no conflict of interest. Emérito Carlos Rodríguez-Merchán is serving as one of the Editorial Board members. We declare that <Emérito Carlos Rodríguez-Merchán> had no involvement in the peer review of this article and has no access to information regarding its peer review. Full responsibility for the editorial process for this article was delegated to <Graham Pawelec>.

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Keywords: Artificial intelligence; Musculoskeletal radiology; Skeletal trauma; Physical and rehabilitation medicine; Orthopedic surgery; Sports medicine

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