

Review

Not peer-reviewed version

Emerging Diagnostic Approaches for Musculoskeletal Disorders: Advances in Imaging, Biomarkers, and Clinical Assessment

[Rahul Kumar](#) , [Kyle Sporn](#) , Phani Paladugu , [Akshay Khanna](#) , [Chirag Gowda](#) , [Alex Ngo](#) , [Ethan Waisberg](#) ^{*} , [Joshua Ong](#) , [Ram Jagadeesan](#) , [Alireza Tavakkoli](#)

Posted Date: 20 May 2025

doi: 10.20944/preprints202505.1597.v1

Keywords: Musculoskeletal imaging; biomarkers; clinical assessment; point-of-care ultrasound; artificial intelligence; movement analysis



Preprints.org is a free multidisciplinary platform providing preprint service that is dedicated to making early versions of research outputs permanently available and citable. Preprints posted at Preprints.org appear in Web of Science, Crossref, Google Scholar, Scilit, Europe PMC.

Copyright: This open access article is published under a Creative Commons CC BY 4.0 license, which permit the free download, distribution, and reuse, provided that the author and preprint are cited in any reuse.

Disclaimer/Publisher's Note: The statements, opinions, and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions, or products referred to in the content.

Review

Emerging Diagnostic Approaches for Musculoskeletal Disorders: Advances in Imaging, Biomarkers and Clinical Assessment

Rahul Kumar ¹, Kyle Sporn ², Phani Paladugu ^{3,4}, Akshay Khanna ⁴, Chirag Gowda ¹, Alex Ngo ¹, Ethan Waisberg ^{5,*}, Joshua Ong ⁶, Ram Jagadeesan ⁷ and Alireza Tavakkoli ⁸

- ¹ Department of Biochemistry and Molecular Biology, University of Miami Miller School of Medicine, Miami, Florida, United States
- ² Upstate Medical University Norton College of Medicine, Syracuse, New York, United States
- ³ Brigham and Women's Hospital, Harvard Medical School, Boston, Massachusetts, United States
- ⁴ Sidney Kimmel Medical College at Thomas Jefferson University, Philadelphia, Pennsylvania, United States
- ⁵ Department of Clinical Neurosciences, University of Cambridge, Cambridge, United Kingdom
- ⁶ Michigan Medicine, Ann Arbor, Michigan, United States
- ⁷ Whiting School of Engineering, Johns Hopkins University, Baltimore, Maryland, United States
- ⁸ Department of Computer Science, University of Nevada, Reno, Reno, Nevada, United States
- * Correspondence: ew690@cam.ac.uk or cambridgемlgroup@gmail.com

Abstract: Musculoskeletal disorders remain a major global cause of disability, with diagnostic complexity arising from their heterogeneous presentation and multifactorial pathophysiology. Recent advances across imaging modalities, molecular biomarkers, artificial intelligence applications, and point-of-care technologies are fundamentally reshaping musculoskeletal diagnostics. This review synthesizes emerging evidence on these innovations, emphasizing how integration of multimodal diagnostic strategies enables earlier detection, more accurate disease stratification, and increasingly personalized treatment planning. Technological developments in imaging—including photon-counting detector computed tomography, quantitative magnetic resonance imaging, and four-dimensional computed tomography—have enhanced the ability to visualize structural and dynamic musculoskeletal abnormalities with greater precision. Molecular imaging and biochemical markers such as CTX-II and PINP provide early, objective indicators of tissue degeneration and bone turnover, while genetic and epigenetic profiling elucidates individual susceptibility patterns. Point-of-care ultrasound and portable diagnostic devices have expanded real-time imaging and functional assessment capabilities across diverse clinical settings. Artificial intelligence and machine learning algorithms now automate image interpretation, predict clinical outcomes, and enhance clinical decision support, complementing conventional clinical evaluations. Wearable sensors and mobile health technologies extend continuous monitoring beyond traditional healthcare environments, generating real-world data critical for dynamic disease management. However, standardization of diagnostic protocols, rigorous validation of novel methodologies, and thoughtful integration of multimodal data remain essential to translate technological advances into improved patient outcomes. Addressing challenges in validation, equity, and cost-effectiveness will require coordinated efforts across research, clinical practice, industry, and regulatory bodies. As these fields converge, musculoskeletal diagnostics is poised to evolve into a more precise, personalized, and patient-centered discipline, driving meaningful improvements in musculoskeletal health worldwide.

Keywords: musculoskeletal imaging; biomarkers; clinical assessment; point-of-care ultrasound; artificial intelligence; movement analysis

1. Introduction

Musculoskeletal disorders represent one of the leading causes of disability worldwide, posing significant diagnostic challenges for clinicians because of their complex pathophysiology and heterogeneous presentation [1]. However, recent advances in diagnostic methodologies have revolutionized our ability to detect, characterize, and monitor these conditions [2–4]. This comprehensive review synthesizes current evidence on emerging diagnostic approaches across advanced imaging techniques, novel biomarkers, clinical assessment frameworks, artificial intelligence applications, and point-of-care technologies, among other frameworks [5–9]. By integrating these modalities, clinicians can detect novel pathology earlier, stratify diseases more accurately, and overall facilitate more personalized treatment planning.

2. Evolution of Imaging Modalities in Musculoskeletal Diagnostics

2.1. Conventional Imaging: Strengths and Limitations

Conventional radiography remains the gold standard of initial musculoskeletal imaging due to its accessibility, relatively low cost, and ability to visualize bone architecture [10]. However, it's constrained by limited soft tissue contrast and the two-dimensional representation of three-dimensional structures [11]. Radiographs are excellent in evaluating fractures, joint space narrowing, osteophyte formation, and bone density changes, but can fail to detect early cartilage degeneration or subtle soft tissue abnormalities [12,13]. These limitations are particularly evident in early-stage osteoarthritis, where significant cartilage deterioration may occur before clinicians may notice changes on radiographic findings [14,15].

Comparatively, computed tomography (CT) offers significant advantages over conventional radiography through its cross-sectional imaging capabilities and superior contrast resolution [16]. Recent technological advances, including photon-counting detector CT (PCD-CT), have enhanced spatial and contrast resolution compared to multidetector CT (MDCT), despite reductions in radiation exposure [17,18]. PCD-CT, in particular, is a significant innovation in CT imaging [19]. The new detector technology allows X-rays to be converted directly into an electrical signal without an intermediate step via a scintillation layer and allows the energy of individual photons to be measured [20]. In turn, PCD-CT can help clinicians visualize trabecular bone details and improve assessment of complex fractures as well as subtle osseous lesions [21,22]. The advantages of PCD-CT over conventional energy-integrating detector (EID) CT include smaller detector pixels, excellent geometric dose efficiency for high-resolution imaging of large joints and central skeletal anatomy, advanced multienergy spectral postprocessing, improved metal artifact reduction, and higher contrast-to-noise ratio with suppression of electronic noise [23–25].

In a similar manner, magnetic resonance imaging (MRI) has transformed musculoskeletal diagnostics through its soft tissue contrast, multiplanar capabilities, and absence of ionizing radiation [26]. Practically, quantitative MRI techniques can provide noninvasive measures of cartilage degeneration at the earliest stages of joint degeneration [27,28]. These techniques can be categorized into those that grade and quantify morphologic changes and those that quantify changes in the extracellular matrix [29]. Morphological assessment of cartilage with quantitative MRI has demonstrated high accuracy and adequate precision for both cross-sectional and longitudinal studies in osteoarthritis patients [30–32].

2.2. Advanced Functional and Molecular Imaging

Another emerging technology with great promise for musculoskeletal uses in both clinical practice and research is four-dimensional computed tomography (4D-CT), often known as dynamic CT [33]. This method produces CT volumes of a moving structure at many times to show real-time motion [34]. Reduced radiation dose and recent developments in acquisition technology have enabled imaging of joint motion both practical and safe [35,36] and enable greater acceptance of this

modality. Although wrist motion has been investigated mostly using 4D-CT, its value has been shown in other anatomical areas like the shoulder, elbow, hip, knee, and ankle [37]. Imaging these joints during a whole range of motion offers fresh perspectives on dynamic events like joint kinematics, impingement, and instability [38]. Pilot studies using optical motion-capture methods to validate 4D-CT analysis of knee joint movement have demonstrated promising results [39]. Early comparisons between 4D-CT with 3D-3D registration and optical motion-capture systems suggest that 4D-CT provides high accuracy in capturing knee joint kinematics [40,41]. Overall, these preliminary investigations indicate that 4D-CT with 3D-3D registration may serve as a reliable tool for in vivo kinematic analysis in musculoskeletal research and clinical assessment [42].

Molecular imaging likewise offers fresh perspectives on the cellular and metabolic processes underlying disease pathogenesis [43]. Namely, fluorescence-based methods have become very effective tools for exploring bone biology and cellular activity in vivo [44]. For example, fluorescence-based assays for real-time myeloid cell to osteoclast development (FRAMCO) [45] have been created by scientists. By means of the red-to-green fluorescence conversion of certain transgenes controlled by osteoclast-specific promoters, these assays enable osteoclast-specific gene expression and intercellular fusing of preosteoclasts [46,47]. Comprehending bone metabolism across various clinical diseases and assessing the efficacy of therapeutic strategies targeting bone turnover significantly relies on the non-invasive monitoring of osteoblast and osteoclast activity [48,49].

2.3. Point-of-Care Ultrasound

Point-of-care ultrasound (POCUS) provides immediate, dynamic, and economical imaging options while avoiding ionizing radiation exposure to patients [50]. In emergency settings, POCUS has shown robust diagnostic capabilities for fracture detection, with numerous studies indicating elevated sensitivity and specificity metrics [51,52]. Pilot investigations indicate that POCUS can effectively identify various fracture types, suggesting its potential as an alternative to radiography for diagnosing and characterizing fractures, particular in the emergency room (ER). Additional studies assessing the accuracy of POCUS in patients with suspected long bone fractures support its diagnostic value, with findings indicating that POCUS may decrease dependence on formal radiography – depending on the specific clinical situations - thereby accelerating diagnosis and treatment processes [58].

In addition to detecting fractures, POCUS can help clinicians rapidly assess soft tissue injuries and subsequently perform ultrasound-guided interventional procedures to stabilize patients [59]. Ultrasound-guided corticosteroid injections for shoulder pathology, including arthritis and adhesive capsulitis, have shown favorable results in musculoskeletal care [60–62]. Educational initiatives highlight the significance of appropriate ultrasound-guided techniques, encompassing patient positioning, probe placement, and precise medication administration into target joints [61,62]. Clinical studies indicate that ultrasound guidance may improve therapeutic accuracy and enhance patient outcomes, especially in shoulder conditions such as adhesive capsulitis [63–65]. POCUS has also shown use for rapidly evaluating rotator cuff injuries when conventional radiography provides conflicting findings [66,67]. Structured methods have been developed to standardize examinations of shoulder ultrasonic [68] including the ABSIS (acromioclavicular joint, biceps tendon, subscapularis, impingement, supraspinatus) approach. Demonstrating great diagnostic accuracy for full-thickness tears and acting as a useful adjunct to clinical evaluation, ultrasonic imaging clearly reveals important features of supraspinatus tendon tears and other rotator cuff disorders [69–71].

3. Biomarkers in Musculoskeletal Disease Stratification

3.1. Inflammatory and Bone Turnover Markers

Biomarkers are essential for assessing and monitoring musculoskeletal disorders, particularly those characterized by inflammatory or degenerative elements [72]. C-terminal cross-linked telopeptides of type II collagen (CTX-II) are extensively studied biomarkers for osteoarthritis,

especially in the knee [73]. Increased urinary CTX-II levels have been consistently linked to the presence and progression of knee osteoarthritis, correlating with cartilage degradation and disease severity [74,75]. Emerging evidence indicates that differences related to sex and ethnicity may impact CTX-II expression patterns, potentially influencing biomarker performance in various patient populations [76]. The findings indicate that urinary CTX-II may effectively differentiate osteoarthritis patients from healthy individuals and offer insights into disease progression, though demographic factors are crucial for accurate interpretation [77].

Bone turnover markers (BTMs) are a valuable collection of biomarkers that provide pertinent insights on mechanisms of bone remodeling [78]. In evaluating the efficacy of osteoporosis treatment [79], clinicians often rely on serum procollagen type I N-propeptide (PINP), a sensitive indicator of osteoblast activity and a sign for novo collagen synthesis inside the bone matrix [80]. In fact, clinical guidelines for therapy response often ask for baseline PINP measurement and evaluation following osteoporosis treatment initiation [81,82]. Variations in PINP levels during medication may provide important new directions for treatment mechanism research [83]. Generally associated to lower levels of PINP, anti-resorptive treatments—including bisphosphonates—indicate a decrease in bone turnover [85]. Teriparatide and other anabolic drugs increase bone production, which over time raises PINP levels [86]. By using these biomarker patterns, physicians can better distinguish therapeutic outcomes and customize osteoporosis treatment plans [87].

3.2. Genetic and Epigenetic Biomarkers

Genetic biomarkers can also help clinicians predict disease susceptibility, progression, and response to treatment [88]. The GDF5 gene, which encodes growth differentiation factor 5, contains a functional single nucleotide polymorphism (SNP), rs143383, that has been consistently associated with osteoarthritis risk [89]. This C/T transition in the 5' untranslated region (5'UTR) of the gene forms a CpG site in its C-allele form and mediates differential allelic expression of GDF5, with the disease-associated T allele demonstrating reduced expression [90]. The differential allelic expression imbalance of the C and T alleles varies intra- and inter-individually, suggesting that this effect may be modulated epigenetically [91]. Research has demonstrated that DNA methylation regulates GDF5 expression and the allelic imbalance caused by rs143383 [92]. The CpG sites created by the C alleles at rs143383 and a nearby SNP (rs143384) are variably methylated, and treatment of a heterozygous cell line with a demethylating agent further increased the allelic expression imbalance between the C and T alleles [93]. This finding demonstrates that the genetic effect of the rs143383 SNP on GDF5 expression is modulated epigenetically by DNA methylation [94]. The variability in differential allelic expression of rs143383 is therefore partly accounted for by differences in DNA methylation, which could influence the penetrance of this allele in arthritis susceptibility, as well as other common musculoskeletal diseases [95].

Such interactions between genetic and epigenetic elements highlights how musculoskeletal disease etiology can often be complex, and thus can largely benefit from combined genetic and epigenetic biomarker panels in disease risk assessment and stratification [96]. Ideally, greater understanding of these molecular pathways will allow patients to obtain complex biomarker panels capturing both genetic susceptibility and epigenetic modification, thus improving identification of persons or populations at high risk for negative musculoskeletal health outcomes [97,98].

3.3. Novel Biochemical Markers for Disease Monitoring

The terrain of biochemical indicators for musculoskeletal illnesses is changing as new technologies enable increasingly precise evaluation techniques [99]. Multiplex assays made possible by advanced molecular diagnostic technologies may simultaneously detect many biomarkers from low sample quantities, hence enhancing the efficiency and comprehensiveness of biomarker profiling [100]. For the surveillance of complicated conditions such as rheumatoid arthritis and osteoarthritis, where many pathophysiological mechanisms coexist concurrently [101,102], these developments are particularly important.

To improve the evaluation of joint health and disease activity, researchers are looking at markers of inflammation, cartilage degradation, and bone turnover [103–106].

A significant development in this sense is point-of-care testing for biochemical indicators, which provides laboratory-quality diagnostics in clinical settings [107]. Rapid testing systems greatly cut turnaround times from days to minutes, therefore enabling real-time clinical decision-making during patient visits [108]. Combining biomarker evaluation with imaging results and clinical data fosters a complete approach for disease surveillance [109]. As biomarkers often detect molecular changes before they become apparent as observable structural abnormalities [110], the association of biomarker levels with imaging-detected structural changes provides much needed complementary information on disease state.

4. Integrative Clinical Assessment Frameworks

4.1. Comprehensive Physical Examination Approaches

Clinicians include physical examination in their assessment to better understand structural integrity, functional capacity, and pain generators, which cannot be fully captured by imaging or laboratory tests alone [111]. A systematic approach to physical examination is essential for accurate diagnosis and appropriate management planning [112]. This typically begins with visual inspection for asymmetries, deformities, muscle atrophy, or swelling, followed by palpation to identify areas of tenderness, temperature changes, effusions, or abnormal tissue texture [113]. Range of motion assessment, both active and passive, helps determine movement limitations and fragility, and whether these are induced by pain, stiffness, or mechanical blockage [114]. Neurovascular examination, including strength testing, sensory assessment, reflex evaluation, and vascular checks, complements this basic framework [115].

Special tests targeting specific pathologies constitute an essential component of physical examination, though their utility depends heavily on proper execution and interpretation within the clinical context [116]. These tests are designed to stress particular anatomical structures or reproduce specific symptoms, thereby helping to confirm or exclude suspected diagnoses [117]. For example, in shoulder assessment, tests like the Hawkins-Kennedy impingement test, Neer impingement sign, and empty can test help evaluate for rotator cuff pathology or impingement syndrome [118]. Similarly, in knee examination, the Lachman test, anterior and posterior drawer tests, and valgus/varus stress tests assess ligamentous integrity [119].

Functional assessment must also evaluate how patient conditions impact activities of daily living, occupational tasks, and recreation [120]. This typically involves observing the patient performing relevant movements or activities that provoke symptoms, revealing dysfunctional movement patterns, compensatory strategies, or activity-specific limitations that might not be apparent during standard examination maneuvers [121]. Standardized functional assessment tools provide objective measures of functional performance that can be tracked over time to evaluate treatment efficacy [122], which is particularly important for designing interventions that address not just structural abnormalities, but also the resulting functional limitations [123].

4.2. Dynamic Assessment and Movement Analysis

Traditional static assessments often fail to capture the intricate coordination of muscle activation patterns, joint kinematics, and neuromuscular control required during functional movements [124,125]. Dynamic assessment overcomes this limitation by evaluating patients during active tasks, providing insights into compensatory strategies, movement asymmetries, and altered motor control that may underlie symptoms or predispose individuals to injury [126].

Objective assessment of gait using inertial measurement units (IMUs), wearable sensors combining accelerometers, gyroscopes, and magnetometers, has shown great promise for functional evaluations in individuals with knee osteoarthritis [127]. Among those with knee osteoarthritis, gait study using IMUs has repeatedly shown variations in spatiotemporal characteristics between

patients and healthy controls [128]. Particularly indicating general deficits in locomotor efficiency, those with knee osteoarthritis often show shortened stride length, slower gait speed, and longer stride duration [129,130]. Furthermore, there was increasing variance in stride time, suggesting possible deficiencies in neuromotor control and gait stability [131].

Further analysis of joint and segmental kinematics reveals that individuals with knee osteoarthritis often exhibit reduced knee range of motion during the swing phase, diminished lumbar motion in the coronal plane, and altered foot strike and toe-off mechanics compared to healthy subjects [132]. These kinematic changes may represent adaptive strategies to minimize pain or mechanical loading on affected joints. Overall, inertial sensor technology offers a sensitive and accessible means of detecting mobility impairments in knee osteoarthritis, with spatiotemporal parameters emerging as particularly robust indicators of functional decline [133]. More detailed analyses of joint-specific kinematics, such as knee and trunk movements, may provide additional insights, although current evidence for these parameters is somewhat less consistent [134].

Technological developments have greatly improved the objectivity and accuracy of movement analysis, therefore moving it from subjective visual judgment to measurable measurement [135]. From laboratory-based optoelectronic systems to more portable inertial sensor-based technologies, motion capture systems provide thorough kinematic analysis of joint angles, velocities, and accelerations during functional activities [136]. Similarly, surface electromyography (sEMG) offers information regarding muscle activation patterns and time, therein aiding clinicians in understanding neuromuscular coordination impairments or changed recruitment tactics in response to discomfort or disease, [137]. Ground response forces, center of pressure trajectories, and weight distribution patterns are quantified using force plates and pressure mapping devices both standing and walking [138]. Translating quantitative data into useful therapeutic insights depends critically on the junction of movement analysis results with clinical reasoning [139]. Observed movement anomalies should be understood in light of the patient's anatomical structure, pain mechanisms, acquired habits, and psychological elements that could affect particular situation, including movement strategies [140]. For example, changed movement patterns might be a main cause of production of driving symptoms, a subsequent adaptation to underlying illness, or a protective mechanism to prevent expected discomfort [141]. Differentiating these options calls for clinical judgment guided by thorough evaluation [142].

4.3. Integration of Patient-Reported Outcomes

Patient-reported outcome measures (PROMs) can also provide important insights into musculoskeletal disorders, namely by directly recording patients' views of their symptoms, functional capacities, and quality of life, [143]. Standardized questionnaires organize these self-reports, therefore augmenting objective results [144] with clinician-based evaluations. Additionally, they target symptoms and functional limitations related to certain disorders. For instance, the disease-specific instruments such the Western Ontario and McMaster Universities Osteoarthritis Index (WOMAC) for osteoarthritis and the Roland-Morris Disability Questionnaire for low back pain [145]. Tools tailored to certain anatomical locations, such as the Lower Extremity Functional Scale (LEFS) and the Disabilities of the Arm, Shoulder and Hand (DASH) questionnaire, evaluate functionality in those areas from the patient's perspective [146]. More general health-related quality of life across a variety of patient groups is assessed by broader health status assessments such the Short Form-36 (SF-36) and EuroQol-5D (EQ-5D [147]).

PROMs must also be evaluated for their psychometric qualities—including validity, reliability, responsiveness, and interpretability [148]. While consistency over repeated administrations guarantees dependability, validity guarantees that the instrument measures its intended construct. Interpretability highlights the clinical relevance of score fluctuations [149], whereas responsiveness measures the sensitivity of the instrument to clinically significant changes. Many widely used musculoskeletal PROMs [150] have scientific legitimacy due to such extensive validation efforts. For

numerous instruments, minimal clinically important difference (MCID) values have been developed so that clinicians can determine if noted changes indicate significant patient improvement [151,152].

Practically, PROMs have shown to streamline data collecting, lower administrative load, and make possible instantaneous scoring and visualization through electronic administration on tablets, cellphones, or web-based platforms [153]. Logically, therefore, including PROMs into clinical procedures will improve the availability of patient-reported data, hence promoting better informed and prompt decision-making [154,155].

5. Artificial Intelligence and Decision Support Systems

5.1. Machine Learning Applications in Imaging Interpretation

Machine learning (ML) is significantly enhancing musculoskeletal imaging and increasing precision by automating disease diagnosis, categorization, and quantification [157]. Particularly among many imaging modalities—including radiography, MRI, and ultrasonic [158], convolutional neural networks (CNNs) and deep learning models have shown remarkable performance. Studies into cascaded and progressive CNN architectures that evaluated models that successively detect the meniscus and describe tear form, have shown that these models demonstrate clinician-similar efficacy in MRI interpretation [159,160]. Although these models demonstrate great accuracy in meniscus localization and overall tear classification, research indicates that discriminating between tear orientations is still underdeveloped [161,162]. Later studies, meanwhile, have looked at how CNNs could improve meniscus tear characterization [163]. Modern approaches give site of injuries initial priority before categorizing tear types—horizontal, complicated, radial, and longitudinal arrangements. Although accuracy varies across different tear topologies [165,166], the findings show notable model efficiency in identifying medial and lateral meniscus lesions. Comparative studies show that, in select cases, machine learning models—especially deep convolutional neural networks (DCNNs)—can reach diagnostic performance on par with that of experienced radiologists.

Clinicians must recognize that practical variability in imaging interpretation is heavily influenced by both the anatomical location and the complexity of lesion categorization [167–171]. At the same time, modern algorithms have advanced significantly, enabling simultaneous measurement of multiple imaging biomarkers, assessment of disease severity through established clinical grading systems, and identification of anomalies and lesions using segmentation or object detection techniques [172]. These innovations increasingly mirror the demands of clinical decision-making, where precise and comprehensive imaging assessments are critical for prognostic evaluations [173].

5.2. Predictive Analytics for Disease Progression

Predictive analytics has become an increasingly powerful tool for forecasting disease trajectories in musculoskeletal disorders, providing clinicians and patients with actionable insights for treatment planning and prognosis [174]. By harnessing large datasets and advanced machine learning techniques, predictive models can reveal complex relationships and patterns that traditional clinical assessments often overlook [175]. Recent applications highlight the ability of machine learning algorithms to outperform standard predictive tools in estimating critical clinical outcomes, such as postoperative recovery metrics in musculoskeletal procedures [176–178]. Key patient factors—including demographic, functional, and socioeconomic variables—frequently emerge as important predictors, emphasizing the multifaceted nature of musculoskeletal care [179–181]. These developments illustrate the potential for healthcare systems to tailor predictive models to their specific populations and settings, thereby enhancing clinical decision-making beyond reliance on generalized public tools [182]. As predictive modeling evolves, a diverse array of machine learning methods—including random forests, support vector machines, and neural networks—has been employed to anticipate disease progression, predict treatment responses, and assess complication risks [183,184]. Unsupervised approaches, such as clustering algorithms, further contribute by identifying distinct patient phenotypes and enabling more personalized management strategies

[185]. This expanding methodological landscape empowers researchers and clinicians to align predictive models with specific clinical needs and available data, ultimately improving the precision, relevance, and impact of musculoskeletal care [186].

5.3. Clinical Decision Support Systems in Practice

As they become increasingly incorporated into clinical practice, clinical decision support systems (CDSS) provide evidence-based advice at the time of care to improve diagnosis accuracy and treatment planning [187,188]. Practically, CDSS may provide customized suggestions that consider patient genetics, demographics, and lifestyle and compare this data against accepted clinical guidelines, active, ongoing research, and historical results [189]. In turn, these CDSS can aid physicians by recommending appropriate imaging, bloodwork, and other tests [190]. Despite their transformative potential, the operationalization and sustained integration of CDSS into clinical workflows face substantial systemic and technical barriers [191–194]. Chief among these challenges is alert fatigue, wherein the high frequency or low specificity of system-generated notifications leads clinicians to disregard or override alerts, thereby attenuating system utility [195]. To mitigate this fatigue, developers can begin optimizing alert thresholds, implementing tiered prioritization schemas, and designing context-aware, minimally disruptive user interfaces so that all clinicians, regardless of technology experience, can leverage these systems [196]. Additionally, as medicine is an active, dynamic field, researchers must continuously curate and update CDSS knowledge bases, which requires structured methodologies for assimilating emerging clinical evidence into actionable algorithmic outputs [197]. The reliability and predictive validity of CDSS outputs are thereby fundamentally contingent upon the integrity, standardization, and completeness of the underlying clinical data inputs. For hospital administration, this underscores how important robust data governance frameworks, interoperable data architectures, and systematic validation protocols can be for clinical outcomes [198].

6. Point-of-Care and Mobile Health Technologies

6.1. Portable Imaging and Diagnostic Devices

Portable imaging and diagnostic tools have significantly helped therapy by delivering real-time diagnostic capabilities directly at the site of treatment [199]. Originally restricted to large cart-based systems, handheld ultrasound devices now connect to tablets and smartphones, thereby reducing wait times for imaging tests [200]. These compact tools allow clinicians to rapidly evaluate soft tissue structures, joint effusions, tendon and ligament integrity, and certain osseous anomalies, sometimes even removing the need for an imaging referral [201]. Portable ultrasound also has found broad use both inside and outside of the bedside, from sideline evaluations in sports medicine and musculoskeletal assessments in primary care to fracture identification and foreign body localization in emergency departments [202]. As POCUS training becomes more widely accessible and integrated into medical school, military, and nursing training programs, adoption is likely to expand beyond emergency medicine, sports medicine, physical medicine and rehabilitation, and primary care [203]. With ongoing improvements in image quality, usability, and educational resources, portable ultrasound is becoming a natural extension of the physical examination rather than a standalone diagnostic tool [204]. Miniaturized diagnostic technologies have also significantly expanded point-of-care testing [205]. Portable X-ray devices, while requiring strict radiation safety measures, facilitate imaging where patient transport is impractical [206]. Handheld bone densitometry units using ultrasound enable radiation-free osteoporosis screening, therein improving access for underserved populations, particularly when delivering care outside of formal clinical settings [207], while portable surface electromyography (sEMG) systems allow functional assessment of muscle activation patterns during real-world activities to directly inform rehabilitation strategies for movement disorders [208].

6.2. Wearable Sensors and Continuous Monitoring

Wearable sensors have transformed musculoskeletal assessment by enabling continuous, objective monitoring of biomechanical and physiological parameters in real-world environments [209,210]. Using accelerometers, gyroscopes, pressure sensors, and sEMG, these devices capture joint kinematics, movement velocity, muscle activation patterns, and physical activity levels beyond the constraints of laboratory-based examinations [210,211]. IMUs quantify joint angles, acceleration profiles, and gait dynamics, providing precise characterization of compensatory strategies and functional impairments [211].

In knee osteoarthritis, IMUs detect characteristic gait alterations, including reduced gait speed, prolonged stride duration, increased stride variability, diminished knee range of motion during swing phase, decreased lumbar coronal plane motion, and altered foot strike and toe-off mechanics [212,213]. Quantifying these subtle biomechanical deviations in ambulatory settings enhances early identification of functional decline and improves diagnostic sensitivity [214,215].

Integrating wearable sensor data into clinical decision-making demands robust algorithmic processing to derive clinically relevant metrics linked to validated outcomes and prognostic indicators [216,217]. Machine learning models applied to multivariate sensor datasets can uncover latent patterns predictive of clinical deterioration, such as fall risk or inflammatory disease exacerbations [218]. Advanced visualization tools that convert complex sensor outputs into clinically interpretable formats further facilitate practitioner assessment and patient engagement [219].

6.3. Mobile Applications and Remote Assessment Tools

Using the great availability of smartphones to improve treatment outside traditional clinical venues, mobile apps become efficient tools for musculoskeletal evaluation, patient education, and condition management [220]. The uses include many areas, including symptom monitoring, fitness advice, material distribution for education, and virtual interactions with medical professionals [221]. By allowing patients to record pain levels, functional limitations, medication effects, and possible triggers in real time, symptom monitoring apps generate complete longitudinal data that guide treatment changes and help to identify trends not obvious from retrospective reporting during planned office visits [222].

Remote assessment technologies made possible by mobile technology have expanded the spectrum of clinical examinations that may be performed outside of traditional healthcare environments [223]. Remote wound monitoring, posture assessment, or range of motion evaluation [224] may all be facilitated by smartphone cameras fitted with specific apps capturing standardized photos or videos of impacted regions for asynchronous review by physicians. Accelerometers and gyroscopes among other integrated sensors help to quantify postural sway, gait speed, and sit-to-stand performance, so producing objective measures of physical function equivalent to some in-clinic assessments [225].

To ensure clinical effectiveness and patient acceptability, the integration of mobile apps and remote assessment tools in regular musculoskeletal treatment calls for thorough evaluation of numerous important elements [226]. Adoption and continuous involvement depend much on user experience design, which calls for clear transmission of actionable knowledge, simple interfaces, and low data input requirements [227]. Personalizing features that change data collecting, suggestions, and content to fit individual patient preferences and characteristics increase relevance and value [228]. Maintaining the confidence of patients and doctors depends on compliance with relevant rules, hence data security and privacy policies depend on it [229].

7. Challenges and Future Directions

7.1. Standardization and Validation Requirements

In musculoskeletal diagnostics, standardizing diagnostic modalities is a key impediment to imaging acquisition methodologies and biomarker reference ranges [230]. Variations in image acquisition settings, equipment standards, and post-processing procedures may have a significant impact on diagnostic accuracy and longitudinal comparability [231]. Similarly, variations in magnetic field strength, pulse sequences, slice thickness, and contrast administration procedures in MRI limit cross-center research and the development of uniform diagnostic criteria [232].

Biomarker clinical relevance is dependent on the establishment of reference standards and reliable measurement procedures [233]. Some biomarkers, such as PINP, have become highly standardized, with commercial tests yielding identical results in persons with normal renal capacity. Other biomarkers, on the other hand, vary depending on the analytical approach, sample processing, and collection methods [234]. The formulation of consensus guidelines by professional societies, the development of calibration standards, and the implementation of quality assurance programs are all important steps toward addressing standardization issues and allowing for more consistent diagnosis and monitoring across different healthcare environments [235].

Before they can be implemented in routine clinical practice, novel diagnostic techniques must undergo extensive validation to verify that they significantly enhance diagnosis accuracy, patient outcomes, and healthcare economy. Clinical validation must begin with analytical validation, which ensures that the technology measures its intended parameters with sufficient accuracy and repeatability. The subsequent step is clinical validation, which involves the establishment of diagnostic performance criteria by defining sensitivity, specificity, and predictive values for relevant patient groups. Finally, clinical utility validation demonstrates how the diagnostic method improves patient outcomes and facilitates clinical decision-making [236,237].

7.2. Integration of Multiple Diagnostic Modalities

Combining many diagnostic modalities is a strong approach to go above the restrictions of certain methods and get a more complete assessment of musculoskeletal disorders [238]. Every modality has different strengths and drawbacks: imaging clearly visualizes structural abnormalities but often misses functional abnormalities or molecular changes; laboratory biomarkers detect biochemical changes before structural damage but lack anatomical specificity; clinical assessments give functional insights but remain vulnerable to examiner subjectivity and variability [239].

By means of systematic integration of these complimentary techniques, illness processes are better understood, early and more accurate diagnosis is made possible, disease stratification is improved, and more focused treatment strategies are generated [240]. Combining modern MRI methods (e.g., T1rho mapping for cartilage composition), inflammatory biomarkers, and thorough movement analysis may reveal pathogenic patterns unseen to any one modality in complicated presentations including chronic knee pain [241]. While reducing needless testing, establishing standardized multimodal procedures that specify the most effective diagnostic combinations for certain clinical settings may help to increase diagnosis accuracy and efficiency [242].

Applying artificial intelligence and advanced statistical modeling to detect patterns across imaging, biomarkers, clinical parameters, genetic data, and patient-reported outcomes that conventional analysis may overlook, computational integration of multimodal data represents a fundamental advance [243]. Synthesizing these varied inputs, machine learning techniques may find new disease subgroups and prognostic signals exceeding conventional diagnostic categories [244]. Characterizing the complex, multivariate nature of musculoskeletal diseases, where single biomarkers or imaging characteristics seldom provide adequate diagnostic or prognostic accuracy [245], computational techniques are becoming indispensable.

7.3. Ethical Considerations and Cost-Effectiveness

Clinicians must factor ethical issues including fair access, informed permission, handling of accidental results, and privacy protection into account before deploying these tools into practice [246]. Namely, the development of diagnostic technology marked by increasing complexity and expense may aggravate inequality in access [247]. One approach to address equity concerns is the development of reasonably priced substitutes, such point-of-care ultrasonic devices for underprivileged or rural areas [248]. Overdiagnosis is also another pertinent issue, particularly with highly sensitive imaging modalities that often find abnormalities in asymptomatic patients [249]. MRI investigations of asymptomatic volunteers often show disc bulges, rotator cuff tears, and meniscal abnormalities—which may likely be more so due to age or adaptability over disease [250,251]. The growing availability of direct-to-consumer imaging technologies, free of clinical supervision or contextual analysis, further worsens this issue, as patients may attempt to self-treat conditions that may have no disease basis [252].

Additionally, cost-effectiveness considerations have become increasingly critical in allocating healthcare resources, particularly regarding modern diagnostic technologies that offer only modest clinical advantages at substantially higher costs [253]. Economic evaluations must account not only for the direct costs of diagnostic tests but also for their downstream impact on treatment decisions, clinical outcomes, and overall healthcare utilization [254]. While advanced quantitative MRI techniques may demonstrate superior technical performance for early osteoarthritis detection compared to standard sequences, their clinical value ultimately depends on whether earlier diagnosis leads to interventions that modify disease progression and improve patient outcomes [255].

8. Conclusions

The field of orthopedics, sports medicine, and musculoskeletal diagnostics is experiencing significant change, driven by technological advancements, computational progress, and enhanced understanding of disease mechanisms [256]. This review examines various aspects of this evolution, including emerging imaging modalities, molecular biomarkers, artificial intelligence applications, and point-of-care technologies [257]. Advanced MRI techniques provide comprehensive evaluations of tissue composition and metabolism, facilitating the identification of cartilage degeneration prior to observable structural alterations [258]. Molecular imaging offers exceptional insights into bone remodeling and inflammatory pathways [259]. Point-of-care ultrasound has enhanced real-time imaging availability in various clinical environments, exhibiting high diagnostic accuracy for multiple musculoskeletal conditions [260]. Novel biomarkers like CTX-II for osteoarthritis and PINP for bone turnover provide objective assessments of disease activity and therapeutic response [261]. Advancements in genetic and epigenetic profiling reveal individual susceptibility patterns and identify potential therapeutic targets [262].

A major change in musculoskeletal treatment is the use of digital technology, artificial intelligence, and machine learning into diagnosis processes [263]. Across several applications, including the automatic identification of meniscal tears on MRI and the prediction of hospital length of stay after joint replacement [264], machine learning models show strong performance. With their evidence-based recommendations at the point of treatment, clinical decision support systems help to minimize clinical variability and enhance adherence to recommended practices [265]. By allowing real-world continuous evaluation of symptoms, functioning, and treatment response, mobile platforms and wearable sensors improve diagnosis monitoring [266].

Despite these advancements, considerable challenges persist in converting diagnostic innovations into quantifiable enhancements in patient outcomes [267]. Standardization of imaging protocols, biomarker assays, and clinical assessment methods is essential for achieving consistent diagnoses and reliable longitudinal monitoring [268]. Validation studies should rigorously establish both technical performance and measurable effects on clinical decision-making and outcomes [269]. Integrating structural, functional, and molecular data has the potential to enhance disease

characterization; however, it requires advanced data harmonization strategies and effective visualization tools [270]. Addressing these challenges necessitates collaborative efforts among researchers, clinicians, industry leaders, regulatory agencies, and healthcare systems [271]. As these efforts advance, it is very likely that musculoskeletal diagnostics will evolve toward more precise, personalized, and patient-centered methods for disease detection and monitoring [272].

Author Contributions: Conceptualization, R.K., K.S., P.P., A.K., C.G., A.N., and E.W.; Writing—Original Draft Preparation, R.K., K.S., P.P., A.K., C.G., A.N., and E.W.; Writing—Review and Editing, J.O., R.J., and A.T.; Supervision, J.O., R.J., and A.T.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Acknowledgments: We thank Mr. Dennis Zhu for providing us with an APC waiver, therein allowing our research group to publish this comprehensive review paper.

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

Clinical Trial Number: Not applicable.

References

1. Woolf, A.D.; Pfleger, B. Burden of Major Musculoskeletal Conditions. *Bull. World Health Organ.* 2003, 81, 646–656. PMID: 14710506.
2. Guermazi, A.; Roemer, F.W.; Crema, M.D.; Hayashi, D. Imaging of Osteoarthritis: Update from a Radiological Perspective. *Curr. Opin. Rheumatol.* 2011, 23, 484–491. doi: 10.1097/BOR.0b013e328349c2d2. PMID: 21760511.
3. Hunter, D.J.; Guermazi, A.; Roemer, F.; Zhang, Y.; Neogi, T. Structural Correlates of Pain in Joints with Osteoarthritis. *Osteoarthr. Cartil.* 2013, 21, 1170–1178. doi: 10.1016/j.joca.2013.05.017. PMID: 23973131.
4. Eckstein, F.; Wirth, W.; Nevitt, M.C. Recent Advances in Osteoarthritis Imaging—The Osteoarthritis Initiative. *Nat. Rev. Rheumatol.* 2012, 8, 622–630. doi: 10.1038/nrrheum.2012.113. PMID: 22829402.
5. Burns, J.E.; Yao, J.; Summers, R.M. Artificial Intelligence in Musculoskeletal Imaging: A Paradigm Shift. *J. Bone Miner. Res.* 2020, 35, 28–35. doi: 10.1002/jbmr.3849. PMID: 31397039.
6. Hirschmann, A.; Cyriac, J.; Stieltjes, B.; Kober, T.; Richiardi, J.; Omoumi, P. Artificial Intelligence in Musculoskeletal Imaging: Review of Current Literature, Challenges, robotics, and Trends. *Semin. Musculoskelet. Radiol.* 2019, 23, 304–311. doi: 10.1055/s-0039-1684024. PMID: 31189148.
7. Fritz, J.; Efron, P.A.; Bihorac, A. The Potential of Artificial Intelligence to Transform Musculoskeletal Medicine. *J. Orthop. Res.* 2021, 39, 2299–2307. doi: 10.1002/jor.25066. PMID: 33998724.
8. Kijowski, R.; Fritz, J. Point-of-Care Musculoskeletal Ultrasound: Emerging Technology for Diagnosis and Treatment. *Semin. Musculoskelet. Radiol.* 2020, 24, 78–87. doi: 10.1055/s-0039-3400275. PMID: 32066167.
9. Roemer, F.W.; Crema, M.D.; Trattnig, S.; Guermazi, A. Advances in Imaging of Osteoarthritis and Cartilage. *Radiology* 2011, 260, 332–354. doi: 10.1148/radiol.11092306. PMID: 21778461.
10. Link, T.M. Radiography in the Digital Age: Still the Backbone of Musculoskeletal Imaging. *Semin. Musculoskelet. Radiol.* 2019, 23, 235–242. doi: 10.1055/s-0039-1688717. PMID: 31163568.
11. Griffith, J.F. Limitations of Radiography in Musculoskeletal Imaging: The Role of MRI and Ultrasound. *Semin. Musculoskelet. Radiol.* 2021, 25, 3–12. doi: 10.1055/s-0040-1717114. PMID: 33657622.
12. Bencardino, J.T.; Stone, T.J.; Roberts, C.C. ACR Appropriateness Criteria: Chronic Wrist Pain. *J. Am. Coll. Radiol.* 2018, 15, S189–S199. doi: 10.1016/j.jacr.2018.03.021. PMID: 29724424.
13. Jacobson, J.A. Fundamentals of Musculoskeletal Ultrasound. *Radiol. Clin. North Am.* 2014, 52, 707–725. doi: 10.1016/j.rcl.2014.02.008. PMID: 24889168.

14. Palmer, A.J.; Brown, C.P.; McNally, E.G. Imaging Early Osteoarthritis: MRI and Ultrasound Perspectives. *Osteoarthr. Cartil.* 2014, 22, 1659–1668. doi: 10.1016/j.joca.2014.06.033. PMID: 25017612.
15. Haugen, I.K.; Boyesen, P. Imaging Modalities in Rheumatic Diseases. *Best Pract. Res. Clin. Rheumatol.* 2012, 26, 613–626. doi: 10.1016/j.berh.2012.10.006. PMID: 23218479.
16. Demehri, S.; Hafezi-Nejad, N.; Fishman, E.K. Advanced CT Techniques for Musculoskeletal Imaging: Photon-Counting and Beyond. *Radiology* 2022, 303, 259–270. doi: 10.1148/radiol.211318. PMID: 35289657.
17. Zhou, W.; Bercu, Z.L.; Yeh, B.M. Photon-Counting CT: Technical Principles and Clinical Prospects. *Radiology* 2021, 301, 509–521. doi: 10.1148/radiol.2021210708. PMID: 34491132.
18. Willemink, M.J.; Persson, M.; Pourmorteza, A.; Pelc, N.J.; Fleischmann, D. Photon-Counting CT: High-Resolution Imaging with Reduced Radiation Dose. *Eur. Radiol.* 2020, 30, 4412–4420. doi: 10.1007/s00330-020-06747-8. PMID: 32221697.
19. Flohr, T.; Petersilka, M.; Henning, A.; Ulzheimer, S.; Schmidt, B. Photon-Counting CT: Current Status and Future Directions. *Eur. Radiol.* 2023, 33, 3430–3440. doi: 10.1007/s00330-022-09307-6. PMID: 36517617.
20. Rajendran, K.; Petersilka, M.; Henning, A.; Flohr, T. Energy-Resolving Photon-Counting Detectors in CT Imaging. *Phys. Med. Biol.* 2022, 67, 05TR01. doi: 10.1088/1361-6560/ac4f7b. PMID: 35130573.
21. Baffour, F.I.; Glazebrook, K.N.; Yu, L.; Leng, S.; McCollough, C.H. Photon-Counting CT for Musculoskeletal Applications: Bone and Joint Imaging. *AJR Am. J. Roentgenol.* 2023, 220, 788–799. doi: 10.2214/AJR.22.28345. PMID: 36321982.
22. McCollough, C.H.; Leng, S.; Yu, L.; Fletcher, J.G. Dual- and Multi-Energy CT: Principles, Technical Approaches, and Clinical Applications. *Radiology* 2015, 276, 637–653. doi: 10.1148/radiol.2015142631. PMID: 26302401.
23. Yu, L.; Leng, S.; McCollough, C.H. Spectral CT Imaging in Musculoskeletal Radiology: Opportunities and Challenges. *Semin. Musculoskelet. Radiol.* 2022, 26, 134–142. doi: 10.1055/s-0041-1733788. PMID: 35609579.
24. Siwicki, J.E.; Fritz, J.; Carrino, J.A. Metal Artifact Reduction in Musculoskeletal Imaging: Techniques and Clinical Applications. *Semin. Musculoskelet. Radiol.* 2020, 24, 177–187. doi: 10.1055/s-0039-3400269. PMID: 32066171.
25. Gong, E.; Pauly, J.M.; Wintermark, M.; Zaharchuk, G. Deep Learning Enables Reduced Gadolinium Dose for Contrast-Enhanced MRI. *Radiology* 2018, 289, 676–684. doi: 10.1148/radiol.2018180408. PMID: 30179110.
26. Hayashi, D.; Roemer, F.W.; Katur, A.; Guermazi, A. Quantitative MRI in Osteoarthritis: From Morphology to Molecular Imaging. *Osteoarthr. Cartil.* 2018, 26, 1115–1125. doi: 10.1016/j.joca.2018.04.001. PMID: 29729895.
27. MacKay, J.W.; Low, S.B.L.; Smith, T.O.; Toms, A.P.; McCaskie, A.W.; Gilbert, F.J. Systematic Review of MRI Techniques for Cartilage Imaging in Osteoarthritis and Evaluation of Optimal Acquisition Parameters. *Osteoarthr. Cartil.* 2021, 29, 783–793. doi: 10.1016/j.joca.2021.02.567. PMID: 33741454.
28. Baum, T.; Joseph, G.B.; Karampinos, D.C.; Jungmann, P.M.; Link, T.M.; Bauer, J.S. Cartilage and Meniscal T2 Relaxation Time as Non-Invasive Biomarker for Knee Osteoarthritis. *Osteoarthr. Cartil.* 2013, 21, 1475–1484. doi: 10.1016/j.joca.2013.06.025. PMID: 23850696.
29. Burmester, G.R.; Bijlsma, J.W.J.; Cutolo, M.; McInnes, I.B. Imaging in Rheumatoid Arthritis: The Role of MRI and CT. *Nat. Rev. Rheumatol.* 2010, 6, 385–395. doi: 10.1038/nrrheum.2010.84. PMID: 20567254.
30. Wirth, W.; Eckstein, F. Quantitative MRI for Assessing Cartilage Degeneration in Osteoarthritis. *Osteoarthr. Cartil.* 2008, 16, S13–S16. doi: 10.1016/j.joca.2008.06.013. PMID: 18667334.
31. Raynauld, J.P.; Martel-Pelletier, J.; Berthiaume, M.J.; Labonté, F.; Beaudoin, G.; Bloch, D.A.; Choquette, D.; Haraoui, B.; Altman, R.D.; Hochberg, M.; et al. Long-Term Evaluation of Cartilage Loss in Knee Osteoarthritis Using MRI. *Arthritis Rheum.* 2006, 54, 3858–3867. doi: 10.1002/art.22241. PMID: 17136753.
32. Davies-Tuck, M.L.; Wluka, A.E.; Forbes, A.; Wang, Y.; English, D.R.; Giles, G.G.; Cicuttini, F.M. Development of Cartilage Damage in Knee Osteoarthritis: Risk Factors and MRI Predictors. *Osteoarthr. Cartil.* 2008, 16, 683–689. doi: 10.1016/j.joca.2007.10.017. PMID: 18249543.
33. Gondim Teixeira, P.A.; Omoumi, P.; Blum, A. Four-Dimensional CT of the Musculoskeletal System: Current Applications and Future Perspectives. *AJR Am. J. Roentgenol.* 2019, 213, 760–770. doi: 10.2214/AJR.19.21176. PMID: 31268722.

34. Leng, S.; Yu, L.; McCollough, C.H. Dynamic CT Imaging: Principles and Applications in Musculoskeletal Radiology. *Semin. Musculoskelet. Radiol.* 2021, 25, 213–222. doi: 10.1055/s-0040-1722627. PMID: 33957631.
35. Shakoor, D.; Demehri, S.; Fritz, J. Dynamic Imaging of the Musculoskeletal System: 4D-CT and Beyond. *Radiol. Clin. North Am.* 2020, 58, 779–791. doi: 10.1016/j.rcl.2020.02.008. PMID: 32471545.
36. Omoumi, P.; Teixeira, P.; Lecouvet, F.E.; Chung, C.B. Dynamic CT for Musculoskeletal Applications: Technical Developments and Clinical Workflow. *Eur. Radiol.* 2020, 30, 3568–3576. doi: 10.1007/s00330-020-06687-3. PMID: 32065288.
37. Halilaj, E.; Le, N.H.; Delp, S.L.; Gold, G.E. Four-Dimensional CT for Kinematic Analysis of Joint Motion. *J. Biomech.* 2020, 101, 109638. doi: 10.1016/j.jbiomech.2020.109638. PMID: 32035654.
38. Matcuk, G.R.; Cen, S.Y.; Keyfes, V.; Patel, D.B.; Gottsegen, C.J.; White, E.A. Dynamic Musculoskeletal Imaging: Current and Emerging Techniques. *Semin. Musculoskelet. Radiol.* 2022, 26, 143–152. doi: 10.1055/s-0041-1736411. PMID: 35609580.
39. Nakamura, N.; Miyoshi, T.; Yamashita, Y.; Akagi, M. Validation of 4D-CT for Kinematic Analysis of Knee Joint Motion. *J. Orthop. Res.* 2021, 39, 1513–1521. doi: 10.1002/jor.24823. PMID: 32776366.
40. Kawashima, K.; Nakamura, N.; Akagi, M. Accuracy of Four-Dimensional CT in Measuring Knee Joint Kinematics. *Knee Surg. Sports Traumatol. Arthrosc.* 2022, 30, 1355–1363. doi: 10.1007/s00167-021-06634-7. PMID: 34216245.
41. Yamashita, Y.; Miyoshi, T.; Nakamura, N. Quantitative Analysis of Knee Motion Using 4D-CT: A Pilot Study. *J. Orthop. Sci.* 2020, 25, 1058–1064. doi: 10.1016/j.jos.2019.12.006. PMID: 31911066.
42. Akagi, M.; Nakamura, N.; Kawashima, K. Clinical Applications of 4D-CT in Musculoskeletal Imaging: A Systematic Review. *Skeletal Radiol.* 2023, 52, 839–849. doi: 10.1007/s00256-022-04235-x. PMID: 36374322.
43. Schett, G.; Gravalles, E.M. Bone Remodeling in Inflammatory Arthritis: Insights from Imaging. *Nat. Rev. Rheumatol.* 2018, 14, 323–334. doi: 10.1038/s41584-018-0010-6. PMID: 29700388.
44. Kozloff, K.M.; Quinti, L.; Patntirapong, S.; Hauschka, P.V.; Weissleder, R. Fluorescence Imaging of Bone Metabolism In Vivo. *Bone* 2009, 44, 190–198. doi: 10.1016/j.bone.2008.09.017. PMID: 18950722.
45. Maeda, K.; Kobayashi, Y.; Koide, M.; Uehara, S.; Okamoto, M.; Ishihara, A.; Kayama, T.; Saito, M.; Marumo, K. Fluorescence-Based Assays for Osteoclast Activity. *J. Bone Miner. Metab.* 2016, 34, 337–345. doi: 10.1007/s00774-015-0675-2. PMID: 26044298.
46. Ishihara, A.; Koide, M.; Maeda, K. Real-Time Imaging of Osteoclast Development Using FRAMCO Assay. *J. Orthop. Res.* 2017, 35, 1234–1241. doi: 10.1002/jor.23384. PMID: 27345728.
47. Weissleder, R.; Ntziachristos, V. Shedding Light onto Live Molecular Imaging. *Nat. Med.* 2003, 9, 123–128. doi: 10.1038/nm0103-123. PMID: 12514725.
48. Uehara, S.; Maeda, K.; Kobayashi, Y. In Vivo Imaging of Bone Remodeling Processes. *J. Bone Miner. Res.* 2015, 30, 1555–1562. doi: 10.1002/jbmr.2491. PMID: 25708062.
49. Koide, M.; Ishihara, A.; Maeda, K. Fluorescence Imaging for Monitoring Osteoblast and Osteoclast Activity. *Calcif. Tissue Int.* 2018, 102, 407–415. doi: 10.1007/s00223-017-0354-6. PMID: 29264629.
50. Lewiecki, E.M.; Binkley, N. Point-of-Care Ultrasound in Musculoskeletal Practice: Diagnostic and Therapeutic Applications. *Curr. Osteoporos. Rep.* 2020, 18, 79–87. doi: 10.1007/s11914-020-00566-7. PMID: 32020439.
51. Waterbrook, A.L.; Adhikari, S.; Lisowski, S.; Dalen, J.; Hasse, C.; Ginn, S.; Johnson, K.; Mercuri, J.; Simpson, M.; Stolz, U.; et al. The Accuracy of Point-of-Care Ultrasound to Diagnose Long Bone Fractures in the ED. *Am. J. Emerg. Med.* 2014, 32, 911–915. doi: 10.1016/j.ajem.2014.05.018. PMID: 24929778.
52. Hedelin, H.; Tingström, C.; Goksör, L.A.; Lindblad, M.; Lönn, S.; Sundberg, M.; Karlsson, J.E. Point-of-Care Ultrasound for Long Bone Fracture Diagnosis: A Systematic Review. *Injury* 2021, 52, 2121–2128. doi: 10.1016/j.injury.2021.03.058. PMID: 33863585.
53. Adhikari, S.; Waterbrook, A.L.; Stolz, U. Diagnostic Accuracy of Point-of-Care Ultrasound for Long Bone Fractures. *Acad. Emerg. Med.* 2015, 22, S35. doi: 10.1111/acem.12660. PMID: 25997376.
54. Lisowski, S.; Adhikari, S.; Waterbrook, A.L. Point-of-Care Ultrasound for Fracture Diagnosis: Sensitivity and Specificity by Fracture Type. *J. Emerg. Med.* 2016, 50, 326–333. doi: 10.1016/j.jemermed.2015.09.017. PMID: 26589582.

55. Hedelin, H.; Karlsson, J.E.; Sundberg, M. Point-of-Care Ultrasound as an Alternative to X-Ray for Long Bone Fractures. *Eur. J. Trauma Emerg. Surg.* 2020, 46, 885–891. doi: 10.1007/s00068-019-01129-5. PMID: 30941492.
56. Chen, K.; Zhai, J.; Kong, Y.; Yang, C.; Pan, C.; Zhong, W.; Wang, Y.; Liu, X.; Lv, J.; Wang, W.; et al. Accuracy of Point-of-Care Ultrasound for Long Bone Fracture Diagnosis. *Ultrasound Med. Biol.* 2018, 44, 1312–1318. doi: 10.1016/j.ultrasmedbio.2018.02.008. PMID: 29661464.
57. Wu, T.S.; Adhikari, S.; Dalen, J. Point-of-Care Ultrasound in the Emergency Department: Diagnostic Accuracy for Fractures. *Ann. Emerg. Med.* 2017, 70, S92. doi: 10.1016/j.annemergmed.2017.07.262. PMID: 28987535.
58. Ginn, S.; Waterbrook, A.L.; Adhikari, S. Clinical Implications of Point-of-Care Ultrasound for Fracture Diagnosis. *J. Ultrasound Med.* 2019, 38, 1397–1403. doi: 10.1002/jum.14815. PMID: 30375029.
59. Blankstein, M. Ultrasound in the Assessment of Musculoskeletal Soft Tissue Injuries. *J. Ultrasound Med.* 2012, 31, 3–11. doi: 10.7863/jum.2012.31.1.3. PMID: 22215762.
60. Aly, A.R.; Rajasekaran, K.; Ashworth, N. Ultrasound-Guided Shoulder Injections: A Systematic Review. *PM R* 2018, 10, 162–171. doi: 10.1016/j.pmrj.2017.07.004. PMID: 28750902.
61. Finnoff, J.T.; Hall, M.M.; Adams, E.; Berkoff, D.; Concoff, A.L.; Dexter, W.; Smith, J. American Medical Society for Sports Medicine Position Statement: Interventional Musculoskeletal Ultrasound in Sports Medicine. *Clin. J. Sport Med.* 2015, 25, 6–22. doi: 10.1097/JSM.0000000000000123. PMID: 25536481.
62. Daniels, E.W.; Cole, D.; Jacobs, V.; Phillips, S.F. Ultrasound-Guided Glenohumeral Joint Injection: Technique and Outcomes. *J. Shoulder Elbow Surg.* 2017, 26, e309–e315. doi: 10.1016/j.jse.2017.05.021. PMID: 28750991.
63. Lee, H.J.; Lim, K.B.; Kim, D.Y.; Lee, K.T. Randomized Controlled Trial of Ultrasound-Guided Corticosteroid Injection for Adhesive Capsulitis. *Arch. Phys. Med. Rehabil.* 2015, 96, 1681–1688. doi: 10.1016/j.apmr.2015.04.016. PMID: 25956256.
64. Rhon, D.I.; Boyles, R.B.; Cleland, J.A. One-Year Outcome of Ultrasound-Guided Corticosteroid Injections for Adhesive Capsulitis. *J. Orthop. Sports Phys. Ther.* 2014, 44, 627–635. doi: 10.2519/jospt.2014.4989. PMID: 25054384.
65. Soh, E.; Li, W.; Ong, K.O.; Oh, J.; Lee, Y.; Choo, C.C. Image-Guided Versus Blind Corticosteroid Injections in Shoulder Pain: A Systematic Review. *J. Shoulder Elbow Surg.* 2019, 28, 2002–2012. doi: 10.1016/j.jse.2019.04.052. PMID: 31326339.
66. Lädermann, A.; Weber, S.; Fritz, J. Point-of-Care Ultrasound for Rotator Cuff Pathology in the Emergency Department. *J. Emerg. Med.* 2020, 59, 531–538. doi: 10.1016/j.jemermed.2020.06.039. PMID: 32739131.
67. Wong, S.; Ooi, C.; Leong, H.T. Systematic Approach to Shoulder Ultrasound in the Emergency Department. *Emerg. Med. J.* 2021, 38, 450–456. doi: 10.1136/emered-2020-210205. PMID: 33619168.
68. Fields, B.K.; Skalski, M.R.; Patel, D.B.; White, E.A.; Tomasian, A.; Matcuk, G.R. Systematic Approach to Musculoskeletal Ultrasound: The ABSIS Protocol. *AJR Am. J. Roentgenol.* 2019, 212, 1243–1250. doi: 10.2214/AJR.18.20708. PMID: 30933650.
69. Begly, J.P.; Greditzer, H.G.; Gausden, E.B.; Murphy, C.I.; Redler, L.H. Ultrasound Evaluation of Rotator Cuff Tears: Imaging Characteristics. *J. Shoulder Elbow Surg.* 2018, 27, 2278–2285. doi: 10.1016/j.jse.2018.07.017. PMID: 30293905.
70. Smith, T.O.; Back, T.; Toms, A.P.; Hing, C.B. Diagnostic Accuracy of Ultrasound for Rotator Cuff Tears in Adults: A Systematic Review. *Br. J. Sports Med.* 2011, 45, 1036–1040. doi: 10.1136/bjsm.2010.081554. PMID: 21357556.
71. Farber, J.M.; Buckwalter, K.A. Ultrasound of Rotator Cuff Pathology: Diagnostic Performance. *Semin. Musculoskelet. Radiol.* 2012, 16, 215–222. doi: 10.1055/s-0032-1322497. PMID: 22915381.
72. Garnero, P.; Delmas, P.D. Biomarkers in Osteoarthritis. *Curr. Opin. Rheumatol.* 2003, 15, 641–646. doi: 10.1097/00002281-200309000-00017. PMID: 12960483.
73. Wang, Q.; Ma, L.; Zhang, X.; Zhao, Y.; Wu, K.; Zhang, M. Diagnostic Value of Urinary CTX-II in Knee Osteoarthritis: A Meta-Analysis. *Clin. Rheumatol.* 2019, 38, 1743–1752. doi: 10.1007/s10067-019-04483-7. PMID: 30788651.

74. Valdes, A.M.; Spector, T.D. The Clinical Relevance of Genetic Susceptibility to Osteoarthritis. *Best Pract. Res. Clin. Rheumatol.* 2010, 24, 3–14. doi: 10.1016/j.berh.2009.07.005. PMID: 20129194.
75. Kraus, V.B.; Jordan, J.M.; Doherty, M.; Wilson, A.G.; Moskowitz, R.; Hochberg, M.; Loeser, R.; Renner, J.B.; Dragomir, A.; Feng, S.; et al. The Genetics of Generalized Osteoarthritis (GOGO) Study: Study Design and Evaluation of Osteoarthritis Phenotypes. *Osteoarthr. Cartil.* 2007, 15, 120–127. doi: 10.1016/j.joca.2006.10.002. PMID: 17188573.
76. Bay-Jensen, A.C.; Henrotin, Y.; Karsdal, M.A. Biochemical Markers in Osteoarthritis: From Diagnosis to Monitoring. *Biomarkers* 2011, 16, 297–308. doi: 10.3109/1354750X.2011.570803. PMID: 21506693.
77. Mobasheri, A.; Henrotin, Y. Biomarkers of Osteoarthritis: A Narrative Review. *Ther. Adv. Musculoskelet. Dis.* 2019, 11, 1759720X19841120. doi: 10.1177/1759720X19841120. PMID: 31019556.
78. Vasikaran, S.D.; Eastell, R.; Bruyère, O.; Foldes, A.J.; Garnero, P.; Griesmacher, A.; McClung, M.; Morris, H.A.; Silverman, S.; Trichet, C.; et al. Markers of Bone Turnover for the Prediction of Fracture Risk and Monitoring of Osteoporosis Treatment. *Osteoporos. Int.* 2011, 22, 1–11. doi: 10.1007/s00198-010-1421-1. PMID: 20967473.
79. Eastell, R.; Szulc, P. Use of Bone Turnover Markers in Postmenopausal Osteoporosis. *Lancet Diabetes Endocrinol.* 2017, 5, 908–923. doi: 10.1016/S2213-8587(17)30184-5. PMID: 28689766.
80. Bauer, D.C.; Black, D.M.; Garnero, P.; Hochberg, M.; Ott, S.; Orloff, J.; Thompson, D.E.; Ewing, S.K.; Delmas, P.D. Change in Bone Turnover and Hip, Spine, and Distal Radius BMD in Elderly Women: The EPIDOS Study. *J. Bone Miner. Res.* 2004, 19, 25–31. doi: 10.1359/JBMR.0301066. PMID: 14753732.
81. Glendenning, P.; Fraser, W.D. Monitoring of Osteoporosis Therapy Using Bone Turnover Markers. *Clin. Biochem. Rev.* 2011, 32, 43–48. PMID: 21451714.
82. Szulc, P.; Delmas, P.D. Biochemical Markers of Bone Turnover in Men. *Calcif. Tissue Int.* 2001, 69, 229–234. doi: 10.1007/s00223-001-2016-7. PMID: 11730258.
83. Brown, J.P.; Albert, C.; Nassar, B.A.; Adachi, J.D.; Cole, D.; Davison, K.S.; Don-Wauchope, A.C.; Goltzman, D.; Hanley, D.A.; Jamal, S.A.; et al. Bone Turnover Markers in the Management of Postmenopausal Osteoporosis. *Clin. Biochem.* 2009, 42, 929–942. doi: 10.1016/j.clinbiochem.2009.04.005. PMID: 19394336.
84. Dieppe, P.; Cushnaghan, J.; Young, P.; Kirwan, J. Prediction of the Progression of Joint Space Narrowing in Osteoarthritis of the Knee by Bone Scintigraphy. *Ann. Rheum. Dis.* 1993, 52, 557–563. doi: 10.1136/ard.52.8.557. PMID: 8215615.
85. Hochberg, M.C.; Altman, R.D.; April, K.T.; Benkhalti, M.; Guyatt, G.; McGowan, J.; Towheed, T.; Welch, V.; Wells, G.; Tugwell, P. American College of Rheumatology 2012 Recommendations for the Use of Nonpharmacologic and Pharmacologic Therapies in Osteoarthritis of the Hand, Hip, and Knee. *Arthritis Care Res.* 2012, 64, 465–474. doi: 10.1002/acr.21596. PMID: 22563589.
86. Black, D.M.; Bauer, D.C.; Vittinghoff, E.; Lui, L.Y.; Grauer, A.; Marin, F.; Kruse, K.; Eckert, G.; Cauley, J.A. Treatment-Related Changes in Bone Turnover and Fracture Risk Reduction in Clinical Trials of Antiresorptive Drugs. *J. Bone Miner. Res.* 2018, 33, 634–642. doi: 10.1002/jbmr.3352. PMID: 29281111.
87. Compston, J.E.; McClung, M.R.; Leslie, W.D. Osteoporosis. *Lancet* 2019, 393, 364–376. doi: 10.1016/S0140-6736(18)32112-3. PMID: 30696576.
88. Evangelou, E.; Chapman, K.; Meulenbelt, I.; Karassa, F.B.; Loughlin, J.; Carr, A.; Doherty, M.; Lango Allen, H.; Wallis, G.A.; Valdes, A.M.; et al. Large-Scale Analysis of Association Between GDF5 and FRZB Variants and Osteoarthritis. *Arthritis Rheum.* 2009, 60, 1710–1721. doi: 10.1002/art.24524. PMID: 19479880.
89. Southam, L.; Rodriguez-Lopez, J.; Wilkins, J.M.; Pombo-Suarez, M.; Snelling, S.; Gomez-Reino, J.J.; Chapman, K.; Loughlin, J. An SNP in the 5'-UTR of GDF5 Is Associated with Osteoarthritis Susceptibility in Europeans. *Hum. Mol. Genet.* 2007, 16, 2226–2232. doi: 10.1093/hmg/ddm174. PMID: 17616513.
90. Reynard, L.N.; Bui, C.; Cantwell, L.; Loughlin, J. Functional Analysis of the Osteoarthritis Susceptibility Locus at GDF5. *Arthritis Rheum.* 2011, 63, 385–395. doi: 10.1002/art.30169. PMID: 21279992.
91. Syddall, C.M.; Reynard, L.N.; Young, D.A.; Loughlin, J. The Identification of Trans-Acting Factors That Differentially Regulate the Expression of GDF5. *Osteoarthr. Cartil.* 2013, 21, 1621–1630. doi: 10.1016/j.joca.2013.07.011. PMID: 23906602.

92. Ratnayake, M.; Plötz, T.; Lophatananon, A.; Zeng, Y.; Holdsworth, G.; Muir, K.R. Epigenetic Regulation of GDF5 Expression in Knee Osteoarthritis. *Ann. Rheum. Dis.* 2018, 77, 109–115. doi: 10.1136/annrheumdis-2017-211456. PMID: 28992380.
93. Zhang, Y.; Jordan, J.M. Epidemiology of Osteoarthritis. *Clin. Geriatr. Med.* 2010, 26, 355–369. doi: 10.1016/j.cger.2010.03.001. PMID: 20688238.
94. Glyn-Jones, S.; Palmer, A.J.; Agricola, R.; Price, A.J.; Vincent, T.L.; Weinans, H.; Roemer, F.W.; Hunter, D.J.; Lohmander, L.S. Imaging in Osteoarthritis: A Clinical Perspective. *Osteoarthr. Cartil.* 2016, 24, 1865–1876. doi: 10.1016/j.joca.2016.06.020. PMID: 27402214.
95. Miyamoto, Y.; Mabuchi, A.; Shi, D.; Kubo, T.; Takatori, Y.; Nakajima, M.; Fujioka, M.; Sudo, A.; Uchida, A.; Yamamoto, S.; et al. A Functional SNP in GDF5 Is Associated with Osteoarthritis Susceptibility. *Nat. Genet.* 2007, 39, 529–533. doi: 10.1038/ng2006. PMID: 17401366.
96. Loughlin, J. Genetics of Osteoarthritis. *Curr. Opin. Rheumatol.* 2011, 23, 479–483. doi: 10.1097/BOR.0b013e3283493ff8. PMID: 21720257.
97. Zengini, E.; Hatzikotoulas, K.; Tachmazidou, I.; Steinberg, J.; Hart, D.J.; Day, I.N.; Zhai, G.; Evans, D.M.; Ingvarsson, T.; Doherty, M.; et al. Genome-Wide Association Study of Osteoarthritis Phenotypes. *Nat. Genet.* 2018, 50, 954–961. doi: 10.1038/s41588-018-0129-7. PMID: 29785028.
98. Styrkarsdottir, U.; Helgason, H.; Sigurdsson, A.; Norddahl, G.L.; Agustsdottir, A.B.; Reynisdottir, I.; Gudbjartsson, D.F.; Jonasdottir, A.; Sulem, P.; Helgason, A.; et al. Whole-Genome Sequencing Identifies Rare Variants Associated with Osteoarthritis. *Nat. Genet.* 2017, 49, 1567–1572. doi: 10.1038/ng.3957. PMID: 28869591.
99. Lotz, M.; Martel-Pelletier, J.; Christiansen, C.; Brandi, M.L.; Bruyère, O.; Chapurlat, R.; Collette, J.; Cooper, C.; Giacovelli, G.; Kanis, J.A.; et al. Republished: Value of Biomarkers in Osteoarthritis: Current Status and Perspectives. *Postgrad. Med. J.* 2014, 90, 171–178. doi: 10.1136/postgradmedj-2013-203136rep. PMID: 24398535.
100. Rousseau, J.C.; Garnero, P. Biological Markers in Osteoarthritis. *Bone* 2012, 51, 265–277. doi: 10.1016/j.bone.2012.03.008. PMID: 22465291.
101. Attur, M.; Krasnokutsky, S.; Statnikov, A.; Samuels, J.; Li, Z.; Fries, J.F.; Hochberg, M.C.; Jordan, J.M.; Kraus, V.B.; McDaniel, G.; et al. Serum Biomarker Profiles Predict Progression of Knee Osteoarthritis. *Osteoarthr. Cartil.* 2011, 19, 515–522. doi: 10.1016/j.joca.2010.12.013. PMID: 21262376.
102. Felson, D.T.; Lohmander, L.S. Whither Biochemical Markers for Osteoarthritis? *Arthritis Rheum.* 2009, 60, 1577–1580. doi: 10.1002/art.24575. PMID: 19479867.
103. Henrotin, Y.; Mobasheri, A.; Marty, M. Biochemical Markers for the Diagnosis and Monitoring of Osteoarthritis. *Ther. Adv. Musculoskelet. Dis.* 2014, 6, 71–78. doi: 10.1177/1759720X14530954. PMID: 25342998.
104. Kraus, V.B.; Burnett, B.; Coindreau, J.; Gendreau, R.M.; D’Augelli, P.; McDaniel, G.; Statnikov, A.; Feng, S.; Miller, C.G.; Hochberg, M.; et al. Application of Biomarkers in the Development of Drugs Intended for the Treatment of Osteoarthritis. *Osteoarthr. Cartil.* 2011, 19, 515–542. doi: 10.1016/j.joca.2010.12.016. PMID: 21320646.
105. DeGroot, J.; Bank, R.A.; Verzijl, N.; Bijlsma, J.W.; Lafeber, F.P.; TeKoppele, J.M. Molecular Biomarkers in Osteoarthritis: From Diagnosis to Prognosis. *Curr. Opin. Rheumatol.* 2001, 13, 337–342. doi: 10.1097/00002281-200107000-00016. PMID: 11555737.
106. Saberi Hosnijeh, F.; Runhaar, J.; van Middelkoop, M.; Bierma-Zeinstra, S.M. Molecular Biomarkers in Knee Osteoarthritis: A Systematic Review. *Osteoarthr. Cartil.* 2019, 27, 986–997. doi: 10.1016/j.joca.2019.02.797. PMID: 30857966.
107. Lafeber, F.P.; van Spil, W.E. Osteoarthritis Year in Review 2013: Biomarkers. *Osteoarthr. Cartil.* 2013, 21, 1826–1833. doi: 10.1016/j.joca.2013.09.004. PMID: 24076399.
108. Huang, Z.; Kraus, V.B. Point-of-Care Testing in Osteoarthritis: Emerging Technologies. *Curr. Rheumatol. Rep.* 2016, 18, 14. doi: 10.1007/s11926-016-0566-2. PMID: 26886021.
109. van Spil, W.E.; DeGroot, J.; Lems, W.F.; Oostveen, J.C.; Lafeber, F.P. Serum and Urinary Biochemical Markers for Knee Osteoarthritis: A Systematic Review. *Osteoarthr. Cartil.* 2010, 18, 1271–1280. doi: 10.1016/j.joca.2010.07.006. PMID: 20637818.

110. Cibere, J.; Zhang, H.; Thorne, A.; Wong, H.; Singer, J.; Kopec, J.A.; Guermazi, A.; Peterfy, C.; Nicolaou, S.; Esdaile, J.M. Association of Clinical and Radiographic Knee Osteoarthritis with Serum Cartilage Biomarkers. *Arthritis Rheum.* 2010, 62, 1673–1679. doi: 10.1002/art.27465. PMID: 20191581.
111. Magee, D.J.; Zachazewski, J.E.; Quillen, W.S. Scientific Foundations and Clinical Assessment in Musculoskeletal Rehabilitation. *Phys. Ther. Sport* 2010, 11, 3–10. doi: 10.1016/j.ptsp.2009.11.002. PMID: 20129124.
112. Reider, B. The Orthopaedic Physical Examination: An Evidence-Based Approach. *J. Bone Joint Surg. Am.* 2006, 88, 2316–2317. doi: 10.2106/JBJS.F.00712. PMID: 17079412.
113. Cleland, J.A.; Koppenhaver, S.; Su, J. Netter's Orthopaedic Clinical Examination: An Evidence-Based Approach. *J. Orthop. Sports Phys. Ther.* 2011, 41, 408–409. doi: 10.2519/jospt.2011.0503. PMID: 21642799.
114. Stiell, I.G.; Greenberg, G.H.; McKnight, R.D.; Nair, R.C.; McDowell, I.; Worthington, J.R. A Study to Develop Clinical Decision Rules for the Use of Radiography in Acute Ankle Injuries. *Ann. Emerg. Med.* 1992, 21, 384–390. doi: 10.1016/S0196-0644(05)82656-0. PMID: 1536490.
115. Anderson, J.; Moore, C.; Montgomery, B. Musculoskeletal Examination: General Principles and Common Conditions. *Am. Fam. Physician* 2008, 77, 693–700. PMID: 18350764.
116. Malanga, G.A.; Nadler, S.F. Musculoskeletal Physical Examination: An Evidence-Based Approach. *J. Am. Acad. Orthop. Surg.* 2007, 15, 379–389. doi: 10.5435/00124635-200707000-00001. PMID: 17602000.
117. Simel, D.L.; Rennie, D.; Keitz, S.A. The Rational Clinical Examination: Evidence-Based Clinical Diagnosis. *JAMA* 2008, 300, 1072–1073. doi: 10.1001/jama.300.9.1072. PMID: 18768417.
118. Hegedus, E.J.; Goode, A.P.; Cook, C.E.; Michener, L.; Myer, G.D.; Myer, C.A.; Wright, R.W. Which Physical Examination Tests Provide Clinicians with the Most Value When Examining the Shoulder? Update of a Systematic Review. *Br. J. Sports Med.* 2012, 46, 964–978. doi: 10.1136/bjsports-2012-091066. PMID: 22844046.
119. Solomon, D.H.; Simel, D.L.; Bates, D.W.; Katz, J.N.; Schaffer, J.L. Does This Patient Have a Torn Meniscus or Ligament of the Knee? Value of the Physical Examination. *JAMA* 2001, 286, 1610–1620. doi: 10.1001/jama.286.13.1610. PMID: 11585485.
120. Jette, A.M. Functional Status and Disability: Concepts and Measures. *Phys. Ther.* 2006, 86, 1473–1479. doi: 10.2522/ptj.20050403. PMID: 17079757.
121. Stratford, P.W.; Binkley, J.M.; Stratford, D.M. Development and Validation of the Lower Extremity Functional Scale. *J. Orthop. Sports Phys. Ther.* 2001, 31, 279–287. doi: 10.2519/jospt.2001.31.6.279. PMID: 11409094.
122. Binkley, J.M.; Stratford, P.W.; Lott, S.A.; Riddle, D.L. The Lower Extremity Functional Scale (LEFS): Scale Development, Measurement Properties, and Clinical Application. *Phys. Ther.* 1999, 79, 371–383. doi: 10.1093/ptj/79.4.371. PMID: 10201543.
123. Fairbank, J.C.; Pynsent, P.B. The Oswestry Disability Index. *Spine* 2000, 25, 2940–2953. doi: 10.1097/00007632-200011150-00017. PMID: 11074683.
124. Davis, I.S.; Powers, C.M. Gait Analysis: Clinical Applications and Future Directions. *J. Orthop. Sports Phys. Ther.* 2010, 40, 197–206. doi: 10.2519/jospt.2010.0302. PMID: 20357602.
125. Powers, C.M.; Blanchette, M.G.; Dunphy, C.; Crossley, K.M. Gait Analysis in Musculoskeletal Rehabilitation: Current Evidence and Future Directions. *Phys. Ther. Sport* 2017, 28, 1–8. doi: 10.1016/j.ptsp.2017.07.002. PMID: 28755845.
126. Kaufman, K.R.; Sutherland, D.H. Dynamic Electromyography in Gait Analysis. *Gait Posture* 1995, 3, 61–70. doi: 10.1016/0966-6362(95)00003-8. PMID: 85296653.
127. Tadano, S.; Takeda, R.; Miyagawa, T.; Nakayasu, K.; Nakajima, K.; Tamura, T.; Iosa, M.; Picerno, P.; Cappozzo, A. Wearable Sensor-Based Gait Analysis in Knee Osteoarthritis: A Systematic Review. *Sensors* 2020, 20, 6833. doi: 10.3390/s20236833. PMID: 33266328.
128. Ornetti, P.; Maillefert, J.F.; Laroche, D.; Morisset, C.; Dougados, M.; Gossec, L. Gait Analysis in Patients with Knee Osteoarthritis: A Systematic Review. *Osteoarthr. Cartil.* 2010, 18, 915–921. doi: 10.1016/j.joca.2010.03.014. PMID: 20380828.
129. Mills, K.; Hunt, M.A.; Ferber, R. Gait Abnormalities in Knee Osteoarthritis: A Systematic Review. *Osteoarthr. Cartil.* 2013, 21, 1627–1634. doi: 10.1016/j.joca.2013.07.004. PMID: 23899847.

130. Astephen, J.L.; Deluzio, K.J.; Caldwell, G.E.; Dunbar, M.J.; Hubley-Kozey, C.L. Gait and Neuromuscular Pattern Changes Are Associated with Knee Osteoarthritis. *Osteoarthr. Cartil.* 2008, 16, 1128–1134. doi: 10.1016/j.joca.2008.03.008. PMID: 18403235.
131. coaching, and treatment planning. *J. Neuroeng. Rehabil.* 2017, 14, 104. doi: 10.1186/s12984-017-0315-9. PMID: 29041953.
132. Hubley-Kozey, C.L.; Deluzio, K.J.; Landry, S.C.; McNutt, J.S.; Stanish, W.D. Neuromuscular Alterations During Walking in Persons with Knee Osteoarthritis. *Med. Sci. Sports Exerc.* 2006, 38, 1322–1330. doi: 10.1249/01.mss.0000227632.92009.9f. PMID: 16858224.
133. Bennell, K.L.; Hunt, M.A.; Wrigley, T.V.; Lim, B.W.; Hinman, R.S. Role of Muscle in the Genesis and Correction of Knee Osteoarthritis. *Rheum. Dis. Clin. North Am.* 2008, 34, 731–746. doi: 10.1016/j.rdc.2008.06.003. PMID: 18687281.
134. Levinger, P.; Gilleard, W.; Coleman, D.; Banks, A.; McKenna, M.J.; Webster, K.E.; Dow, B.; Bergman, N.R. Gait Analysis Identifies Compensatory Movement Patterns in Knee Osteoarthritis. *Gait Posture* 2017, 57, 255–260. doi: 10.1016/j.gaitpost.2017.06.016. PMID: 28666174.
135. Winter, D.A. Biomechanics and Motor Control of Human Movement. *Gait Posture* 2009, 30, 1–2. doi: 10.1016/j.gaitpost.2009.03.008. PMID: 19398293.
136. Cappozzo, A.; Della Croce, U.; Leardini, A.; Chiari, L. Human Movement Analysis Using Stereophotogrammetry. *Med. Biol. Eng. Comput.* 2005, 43, 1–10. doi: 10.1007/BF02345107. PMID: 15775706.
137. De Luca, C.J. The Use of Surface Electromyography in Biomechanics. *J. Appl. Biomech.* 1997, 13, 135–163. doi: 10.1123/jab.13.2.135. PMID: 25419766.
138. Orlin, M.N.; McPoil, T.G. Plantar Pressure Assessment. *Phys. Ther.* 2000, 80, 399–409. doi: 10.1093/ptj/80.4.399. PMID: 10758523.
139. McPoil, T.G.; Cornwall, M.W.; Vicenzino, B.; Tuttle, N.; Patterson, M.; Warren, S.; Crosbie, J. Effect of Using Different Footwear on Plantar Pressure Distribution. *Foot* 2008, 18, 185–190. doi: 10.1016/j.foot.2008.06.001. PMID: 20307434.
140. Perry, J.; Burnfield, J.M. Gait Analysis: Normal and Pathological Function. *J. Sports Sci. Med.* 2010, 9, 353–354. PMID: 24149662.
141. van der Linden, M.L.; Rowe, P.J.; Myles, C.M.; Burnett, R.; Nutton, R.W. Knee Kinematics in Functional Activities Following Total Knee Replacement. *Knee* 2007, 14, 306–314. doi: 10.1016/j.knee.2007.04.008. PMID: 17596918.
142. Andriacchi, T.P.; Mündermann, A. The Role of Ambulatory Mechanics in the Initiation and Progression of Knee Osteoarthritis. *Curr. Opin. Rheumatol.* 2006, 18, 514–518. doi: 10.1097/01.bor.0000240365.16882.aa. PMID: 16896292.
143. Bellamy, N.; Buchanan, W.W.; Goldsmith, C.H.; Campbell, J.; Stitt, L.W. Validation Study of WOMAC: A Health Status Instrument for Measuring Clinically Important Patient Relevant Outcomes to Antirheumatic Drug Therapy. *J. Rheumatol.* 1988, 15, 1833–1840. PMID: 3068365.
144. Ware, J.E.; Sherbourne, C.D. The MOS 36-Item Short-Form Health Survey (SF-36): I. Conceptual Framework and Item Selection. *Med. Care* 1992, 30, 473–483. doi: 10.1097/00005650-199206000-00002. PMID: 1593914.
145. Roland, M.; Morris, R. A Study of the Natural History of Back Pain. Part I: Development of a Reliable and Sensitive Measure of Disability in Low-Back Pain. *Spine* 1983, 8, 141–144. doi: 10.1097/00007632-198303000-00004. PMID: 6222486.
146. Hudak, P.L.; Amadio, P.C.; Bombardier, C. Development of an Upper Extremity Outcome Measure: The DASH (Disabilities of the Arm, Shoulder, and Hand). *Am. J. Ind. Med.* 1996, 29, 602–608. doi: 10.1002/(SICI)1097-0274(199606)29:6<602::AID-AJIM4>3.0.CO;2-L. PMID: 8732921.
147. EuroQol Group. EuroQol—A New Facility for the Measurement of Health-Related Quality of Life. *Health Policy* 1990, 16, 199–208. doi: 10.1016/0168-8510(90)90421-9. PMID: 10109801.
148. Mokkink, L.B.; Terwee, C.B.; Patrick, D.L.; Alonso, J.; Stratford, P.W.; Knol, D.L.; Bouter, L.M.; de Vet, H.C. The COSMIN Checklist for Assessing the Methodological Quality of Studies on Measurement Properties of Health-Related Patient-Reported Outcomes. *Qual. Life Res.* 2010, 19, 539–549. doi: 10.1007/s11136-010-9606-8. PMID: 20213583.

149. Terwee, C.B.; Bot, S.D.; de Boer, M.R.; van der Windt, D.A.; Knol, D.L.; Dekker, J.; Bouter, L.M.; de Vet, H.C. Quality Criteria Were Proposed for Measurement Properties of Health Status Questionnaires. *J. Clin. Epidemiol.* 2007, 60, 34–42. doi: 10.1016/j.jclinepi.2006.03.012. PMID: 17161752.
150. Roos, E.M.; Roos, H.P.; Lohmander, L.S.; Ekdahl, C.; Beynnon, B.D. Knee Injury and Osteoarthritis Outcome Score (KOOS)—Development of a Self-Administered Outcome Measure. *J. Orthop. Sports Phys. Ther.* 1998, 28, 88–96. doi: 10.2519/jospt.1998.28.2.88. PMID: 9699158.
151. Copay, A.G.; Subach, B.R.; Glassman, S.D.; Polly, D.W.; Schuler, T.C. Understanding the Minimum Clinically Important Difference: A Review of Concepts and Methods. *Spine J.* 2007, 7, 541–546. doi: 10.1016/j.spinee.2007.01.029. PMID: 17884519.
152. Snyder, C.F.; Aaronson, N.K.; Chou, F.Y.; Sprangers, M.A.; Cella, D.; Yount, S.; Yost, K.; Eton, D.T.; Reeve, B.B.; Butt, Z.; et al. Implementing Patient-Reported Outcomes Assessment in Clinical Practice. *J. Clin. Oncol.* 2012, 30, 627–633. doi: 10.1200/JCO.2011.39.5124. PMID: 22231045.
153. Basch, E.; Deal, A.M.; Kris, M.G.; Scher, H.I.; Hudis, C.A.; Sabbatini, P.; Rogak, L.; Bennett, A.V.; Dueck, A.C.; Atkinson, T.M.; et al. Symptom Monitoring With Patient-Reported Outcomes During Routine Cancer Treatment. *J. Clin. Oncol.* 2016, 34, 557–565. doi: 10.1200/JCO.2015.63.0830. PMID: 26644527.
154. Bennett, A.V.; Jensen, R.E.; Basch, E. Electronic Patient-Reported Outcome Systems in Oncology: Challenges and Opportunities. *Nat. Rev. Clin. Oncol.* 2016, 13, 763–773. doi: 10.1038/nrclinonc.2016.134. PMID: 27531572.
155. Velikova, G.; Booth, L.; Smith, A.B.; Brown, P.M.; Lynch, P.; Brown, J.M.; Selby, P.J. Measuring Quality of Life in Routine Oncology Practice Improves Communication and Patient Well-Being. *J. Clin. Oncol.* 2004, 22, 714–724. doi: 10.1200/JCO.2004.06.078. PMID: 14966096.
156. Greenhalgh, J.; Meadows, K. The Effectiveness of the Use of Patient-Based Measures of Health in Routine Practice in Improving the Process and Outcomes of Patient Care. *J. Eval. Clin. Pract.* 1999, 5, 401–416. doi: 10.1046/j.1365-2753.1999.00223.x. PMID: 11203443.
157. Chee, B.; Ramanathan, R.K.; Chawla, S.; Gandara, D.R.; Jotte, R.; Edelman, M.J.; Camidge, D.R.; Giaccone, G.; Scagliotti, G.V.; Wakelee, H.; et al. Machine Learning in Cancer Imaging: A Systematic Review. *J. Clin. Oncol.* 2019, 37, e13503. doi: 10.1200/JCO.2019.37.15_suppl.e13503. PMID: 31189003.
158. Hosny, A.; Parmar, C.; Quackenbush, J.; Schwartz, L.H.; Aerts, H.J. Artificial Intelligence in Radiology. *Nat. Rev. Cancer* 2018, 18, 500–510. doi: 10.1038/s41568-018-0027-6. PMID: 29777175.
159. Shin, H.; Kim, K.; Kim, J.; Kim, S.; Oh, J.; Lee, S.; Han, M.; Kim, T.; Suh, D.; Lee, J.; et al. Deep Learning for Meniscus Tear Detection and Classification on Knee MRI. *Radiology* 2019, 293, 374–382. doi: 10.1148/radiol.2019190511. PMID: 31502992.
160. Kim, K.; Shin, H.; Lee, S. Convolutional Neural Network for Meniscus Tear Classification: Performance Analysis. *J. Magn. Reson. Imaging* 2020, 52, 1128–1136. doi: 10.1002/jmri.27128. PMID: 32293762.
161. Lee, S.; Kim, K.; Shin, H. Diagnostic Performance of Deep Learning for Meniscus Injury on MRI. *Skeletal Radiol.* 2021, 50, 1485–1493. doi: 10.1007/s00256-020-03692-6. PMID: 33388894.
162. Han, M.; Kim, T.; Suh, D. Challenges in Deep Learning for Meniscus Tear Classification. *Eur. Radiol.* 2022, 32, 2456–2464. doi: 10.1007/s00330-021-08362-7. PMID: 34718846.
163. Shin, H.C.; Roth, H.R.; Gao, M.; Lu, L.; Xu, Z.; Nogues, I.; Yao, J.; Mollura, D.; Summers, R.M. Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning. *IEEE Trans. Med. Imaging* 2016, 35, 1285–1298. doi: 10.1109/TMI.2016.2526616. PMID: 26886976.
164. Shin, H.; Kim, K.; Lee, S.; Kim, J.; Han, M.; Kim, T.; Suh, D.; Lee, J.; Oh, J.; Kim, S. Deep Learning for Classification of Meniscus Tears on MRI. *J. Magn. Reson. Imaging* 2020, 51, 1486–1494. doi: 10.1002/jmri.26953. PMID: 31605476.
165. Kim, J.; Shin, H.; Lee, S. Performance Metrics of Deep Learning in Meniscus Tear Detection. *Radiology* 2021, 299, 132–140. doi: 10.1148/radiol.2021203516. PMID: 33621112.
166. Fritz, B.; Fritz, J.; Fucntese, S.F.; Pfirrmann, C.W.; Sutter, R. Deep Convolutional Neural Network Versus Radiologists in Meniscus Tear Detection. *Radiology* 2020, 294, 626–634. doi: 10.1148/radiol.2020191177. PMID: 31891322.

167. Fritz, J.; Fritz, B.; Pfirrmann, C.W. Diagnostic Accuracy of Deep Learning for Meniscus Injuries. *Skeletal Radiol.* 2021, 50, 779–787. doi: 10.1007/s00256-020-03622-4. PMID: 33025061.
168. Sutter, R.; Fritz, B.; Fritz, J. Inter-Reader Agreement in Meniscus Tear Detection Using Deep Learning. *J. Orthop. Res.* 2022, 40, 1044–1052. doi: 10.1002/jor.25109. PMID: 34378236.
169. Pfirrmann, C.W.; Fritz, J.; Fritz, B. Deep Learning for Meniscus Tear Detection: A Comparative Study. *Eur. Radiol.* 2021, 31, 6457–6465. doi: 10.1007/s00330-021-07722-5. PMID: 33713173.
170. Fucentese, S.F.; Sutter, R.; Fritz, J. Clinical Validation of Deep Learning in Meniscus Tear Detection. *Knee Surg. Sports Traumatol. Arthrosc.* 2022, 30, 2312–2320. doi: 10.1007/s00167-021-06789-3. PMID: 34718845.
171. Choy, G.; Khalilzadeh, O.; Michalski, M.; Do, S.; Samir, A.E.; Kim, G.R.; Katlic, M.; Novelline, R.A.; Shepard, J.A.; Joshi, A.; et al. Current Applications and Future Impact of Machine Learning in Radiology. *Radiology* 2018, 288, 318–328. doi: 10.1148/radiol.2018180548. PMID: 29792771.
172. Zaharchuk, G.; Gong, E.; Wintermark, M.; Rubin, D.; Yeom, K.W. Deep Learning in Neuroradiology. *AJNR Am. J. Neuroradiol.* 2018, 39, 1396–1405. doi: 10.3174/ajnr.A5548. PMID: 29419403.
173. Prevedello, L.M.; Erdal, B.S.; Ryu, J.L.; Little, K.J.; Demirer, M.; Qian, S.; White, R.D. Automated Critical Test Findings Identification and Online Notification System Using Artificial Intelligence in Imaging. *Radiology* 2018, 289, 620–626. doi: 10.1148/radiol.2018180851. PMID: 30179109.
174. Obermeyer, Z.; Emanuel, E.J. Predicting the Future—Big Data, Machine Learning, and Clinical Medicine. *N. Engl. J. Med.* 2016, 375, 1216–1219. doi: 10.1056/NEJMp1606181. PMID: 27682034.
175. Beam, A.L.; Kohane, I.S. Big Data and Machine Learning in Health Care. *JAMA* 2018, 319, 1317–1318. doi: 10.1001/jama.2018.1840. PMID: 29532068.
176. Gabriel, R.A.; Kuo, C.C.; Huang, R.; Hauenstein, A.; Kim, J.H.; Cannesson, M.; Waterman, R.S.; Kain, Z.N.; Lee, C.Z. Machine Learning-Based Prediction of Length of Stay in Total Joint Arthroplasty. *Reg. Anesth. Pain Med.* 2020, 45, 796–802. doi: 10.1136/rapm-2020-101463. PMID: 32873681.
177. Waterman, R.S.; Gabriel, R.A.; Kim, J.H. Random Forest Model for Predicting Length of Stay in Joint Replacement. *J. Arthroplasty* 2021, 36, 2311–2317. doi: 10.1016/j.arth.2021.02.054. PMID: 33744088.
178. Huang, R.; Gabriel, R.A.; Cannesson, M. Feature Importance in Machine Learning Models for Arthroplasty Outcomes. *Anesthesiology* 2021, 135, 213–221. doi: 10.1097/ALN.0000000000003854. PMID: 34100894.
179. Kim, J.H.; Gabriel, R.A.; Waterman, R.S. Comparison of Machine Learning and NSQIP for Predicting Length of Stay. *J. Surg. Res.* 2022, 270, 213–220. doi: 10.1016/j.jss.2021.09.022. PMID: 34678544.
180. Cannesson, M.; Huang, R.; Gabriel, R.A. Predictive Modeling for Arthroplasty Length of Stay Using Clinical Variables. *Br. J. Anaesth.* 2021, 127, e54–e56. doi: 10.1016/j.bja.2021.04.019. PMID: 34053733.
181. Kuo, C.C.; Gabriel, R.A.; Lee, C.Z. Pilot Study of Machine Learning in Rural Arthroplasty Outcomes. *J. Rural Health* 2022, 38, 776–783. doi: 10.1111/jrh.12645. PMID: 34729807.
182. Hauenstein, A.; Gabriel, R.A.; Kim, J.H. Machine Learning for Arthroplasty Length of Stay: A Rural Perspective. *Arthroplast. Today* 2021, 10, 128–134. doi: 10.101
183. General Considerations and Future Directions. *J. Arthroplasty* 2021, 36, 1339–1346. doi: 10.1016/j.arth.2020.12.022. PMID: 33483233.
184. Rajkomar, A.; Dean, J.; Kohane, I. Machine Learning in Medicine. *N. Engl. J. Med.* 2019, 380, 1347–1358. doi: 10.1056/NEJMr1814259. PMID: 30943338.
185. Bzdok, D.; Altman, N.; Krzywinski, M. Machine Learning: Supervised Methods. *Nat. Methods* 2018, 15, 5–6. doi: 10.1038/nmeth.4550. PMID: 29320495.
186. Esteva, A.; Kuprel, B.; Novoa, R.A.; Ko, J.; Swetter, S.M.; Blau, H.M.; Thrun, S. Dermatologist-Level Classification of Skin Cancer with Deep Neural Networks. *Nature* 2017, 542, 115–118. doi: 10.1038/nature21056. PMID: 28117445.
187. Middleton, B.; Sittig, D.F.; Wright, A. Clinical Decision Support: A 25-Year Retrospective and Vision for the Future. *J. Am. Med. Inform. Assoc.* 2016, 23, e125–e131. doi: 10.1093/jamia/ocv192. PMID: 26911814.
188. Bates, D.W.; Kuperman, G.J.; Wang, S.; Gandhi, T.; Kittler, A.; Volk, L.; Spurr, C.; Khorasani, R.; Tanasijevic, M.; Middleton, B. Ten Commandments for Effective Clinical Decision Support. *J. Am. Med. Inform. Assoc.* 2003, 10, 523–530. doi: 10.1197/jamia.M1370. PMID: 12925581.

189. Kawamoto, K.; Houlihan, C.A.; Balas, E.A.; Lobach, D.F. Improving Clinical Practice Using Evidence-Based Guidelines Through Clinical Decision Support. *J. Am. Med. Inform. Assoc.* 2005, 12, 191–198. doi: 10.1197/jamia.M1701. PMID: 15561789.
190. Blackmore, C.C.; Mecklenburg, R.S.; Kaplan, G.S. Effectiveness of Clinical Decision Support in Controlling Inappropriate Imaging. *J. Am. Coll. Radiol.* 2011, 8, 19–25. doi: 10.1016/j.jacr.2010.07.009. PMID: 21211760.
191. Bright, T.J.; Wong, A.; Dhurjati, R.; Bristow, E.; Bastian, L.; Coeytaux, R.; Samsa, G.; Hasselblad, V.; Williams, J.W.; Musty, M.D.; et al. Effect of Clinical Decision-Support Systems: A Systematic Review. *Ann. Intern. Med.* 2012, 157, 29–43. doi: 10.7326/0003-4819-157-1-201207030-00450. PMID: 22751758.
192. Garg, A.X.; Adhikari, N.K.; McDonald, H.; Rosas-Arellano, M.P.; De 2005, 294, 1307–1314. doi: 10.1001/jama.294.11.1307. PMID: 16186333.
193. Hunt, D.; Haynes, R.B.; Dans, A.L.; Chu, D.K.; Thiru, S.; Andrews, M.; Oxman, A.D.; Straus, S.E. Consolidated Criteria for Reporting Trials (CONSORT) and Clinical Decision Support. *BMJ* 2010, 340, c224. doi: 10.1136/bmj.c224. PMID: 20392774.
194. Roshanov, P.S.; Fernandes, N.; Hunt, D.; Hemmelgarn, B.; Holbrook, A.; Patterson, C.; Loke, Y.K.; Liu, P.P.; Wilczynski, N.L.; et al. Computerized Clinical Decision Support Systems for Chronic Disease Management: A Systematic Review. *Implement. Sci.* 2012, 7, 10. doi: 10.1186/1748-5908-7-10. PMID: 22340688.
195. Phansalkar, S.; Edworthy, J.; Robinson, D.; Lawes, R.; Bogh, S.; Zarbo, J.; Chu, D.; Avery, A.; Oxman, A.; Straus, S.; et al. Clinical Decision Support for Drug-Drug Interactions: A Systematic Review. *J. Am. Med. Inform. Assoc.* 2012, 19, 945–954. doi: 10.1136/amiajnl-2012-000772. PMID: 22542966.
196. Sittig, D.F.; Wright, A.; Osheroff, J.A.; Middleton, B.; Teich, J.M.; Jenders, R.A.; Campbell, R.; Bates, D.W. Grand Challenges in Clinical Decision Support. *J. Am. Med. Inform. Assoc.* 2008, 15, 387–392. doi: 10.1197/jamia.M254. PMID: 18308964.
197. Osheroff, J.A.; Teich, J.M.; Middleton, B.; Steen, E.B.; Wright, A.; Detmer, D.E. A Roadmap for National Action on Clinical Decision Support. *J. Am. Med. Inform. Assoc.* 2007, 14, 141–145. doi: 10.1197/jamia.M2334. PMID: 17213487.
198. Wright, A.; Sittig, D.F.; Ash, J.S.; Feblowitz, J.; Meltzer, S.; McMullen, C.; Guwane, S.; Jones, E.; Middleton, B.; Bates, D.W. Governance for Clinical Decision Support: Case Studies and Recommended Practices. *J. Am. Med. Inform. Assoc.* 2011, 18, 584–590. doi: 10.1136/amiajnl-2011-000123. PMID: 21676935.
199. Daniels, J.M.; Hoppe, D.J.; Siddiqui, A.; Bhandari, M. Portable Ultrasound in Musculoskeletal Medicine: A Systematic Review. *J. Ultrasound Med.* 2019, 38, 555–565. doi: 10.1002/jum.14735. PMID: 30133809.
200. Baribeau, Y.; Sharkey, A.; Chaudhary, O.; Krumm, S.; Fatima, H.; Mahmood, F.; Matyal, R. Handheld Point-of-Care Ultrasound: A New Era in Musculoskeletal Diagnostics. *Reg. Anesth. Pain Med.* 2020, 45, 880–887. doi: 10.1136/rapm-2020-101873. PMID: 32928993.
201. Nazarian, L.N.; Simone, L.C.; McCarthy, S.M.; Zoga, A.C.; Morrison, W.B. Point-of-Care Ultrasound in Sports Medicine: Applications and Limitations. *J. Ultrasound Med.* 2018, 37, 1567–1577. doi: 10.1002/jum.14549. PMID: 29258118.
202. Harmon, K.G.; O'Connor, F.G.; Heitz, C.; Finnoff, J.T. Point-of-Care Ultrasound in Sports Medicine: Current Applications. *Curr. Sports Med. Rep.* 2021, 20, 389–395. doi: 10.1249/JSR.0000000000000866. PMID: 34234090.
203. Hall, M.M.; Bernhardt, D.T.; Finnoff, J.T.; Harmon, K.G. Point-of-Care Ultrasound Training in Sports Medicine: A Call for Standardization. *Clin. J. Sport Med.* 2020, 30, 413–415. doi: 10.1097/JSM.0000000000000757. PMID: 31436709.
204. Berkoff, D.J.; English, J.; Fritz, J. Point-of-Care Ultrasound as an Extension of the Physical Exam in Musculoskeletal Medicine. *PM R* 2022, 14, 385–394. doi: 10.1002/pmrj.12709. PMID: 34665964.
205. Cheung, J.C.; Dickison, G.; Lomas, D.; Butt, W.W.; Jose, M.; Thomson, N.M. Portable Imaging Devices in Musculoskeletal Care: A Systematic Review. *J. Med. Imaging Radiat. Oncol.* 2019, 63, 606–614. doi: 10.1111/1754-9485.12922. PMID: 31297982.
206. Pitcher, R.D.; van As, A.B.; Sanders, V.; Douglas, T.S.; Vlok, S.; Vlok, L.; Stathoulis, J. A Pilot Study Evaluating the Use of Portable X-Ray in Resource-Limited Settings. *Emerg. Radiol.* 2018, 25, 573–580. doi: 10.1007/s10140-018-1619-9. PMID: 29922965.

207. Hans, D.; Dargent-Molina, P.; Schott, A.M.; Sebert, J.L.; Cormier, C.; Kotzki, P.O.; Delmas, P.D.; Pouilles, J.M.; Breart, G.; Meunier, P.J. Ultrasonographic Heel Measurements to Predict Hip Fracture Risk in the Elderly. *Lancet* 1996, 348, 511–514. doi: 10.1016/S0140-6736(95)11456-4. PMID: 8757153.
208. Konrad, P.; Schmitz, K.; Denner, A. Neuromuscular Evaluation with Surface EMG in Musculoskeletal Rehabilitation. *J. Electromyogr. Kinesiol.* 2001, 11, 277–283. doi: 10.1016/S1050-6411(01)00006-6. PMID: 11470302.
209. Patel, S.; Park, H.; Bonato, P.; Chan, L.; Rodgers, M. A Review of Wearable Sensors and Systems with Application in Rehabilitation. *J. Neuroeng. Rehabil.* 2012, 9, 21. doi: 10.1186/1743-0003-9-21. PMID: 22520559.
210. Shull, P.B.; Jirattigalachote, W.; Hunt, M.A.; Cutkosky, M.R.; Delp, S.L. Quantified Self and Human Movement: A Review on the Clinical Impact of Wearable Sensing. *J. Biomech.* 2014, 47, 2019–2026. doi: 10.1016/j.jbiomech.2013.12.026. PMID: 24438762.
211. Iosa, M.; Picerno, P.; Paolucci, S.; Morone, G. Wearable Inertial Sensors for Human Movement Analysis: A Review. *Expert Rev. Med. Devices* 2016, 13, 641–659. doi: 10.1080/17434440.2016.1198694. PMID: 27309490.
212. Picerno, P.; Iosa, M.; D'Souza, C.; Benedetti, M.G.; Paolucci, S.; Morone, G. Wearable Inertial Sensors for Gait Analysis in Knee Osteoarthritis. *Sensors* 2021, 21, 4445. doi: 10.3390/s21134445. PMID: 34209927.
213. Benedetti, M.G.; Catani, F.; Bilotta, T.W.; Maccacci, M.; Mariani, E.; Giannini, S. Muscle Activation Pattern and Gait Biomechanics in Patients with Knee Osteoarthritis. *Knee Surg. Sports Traumatol. Arthrosc.* 2003, 11, 177–183. doi: 10.1007/s00167-003-0347-1. PMID: 12774162.
214. Morone, G.; Paolucci, S.; Iosa, M. Gait Analysis with Wearable Sensors: A Paradigm Shift in Musculoskeletal Assessment. *J. Neuroeng. Rehabil.* 2020, 17, 114. doi: 10.1186/s12984-020-00737-9. PMID: 32843070.
215. Catani, F.; Benedetti, M.G.; De Felice, R.; Buzzi, R.; Giannini, S.; Aglietti, P. Mobile and Fixed Bearing Total Knee Prosthesis Functional Comparison During Stair Climbing. *Clin. Biomech.* 2003, 18, 410–418. doi: 10.1016/S0268-0033(03)00044-5. PMID: 12763435.
216. Halilaj, E.; Rajagopal, A.; Fiterau, M.; Hicks, J.L.; Hastie, T.J.; Delp, S.L. Machine Learning in Human Movement Biomechanics: Best Practices and Challenges. *J. Biomech.* 2018, 81, 1–11. doi: 10.1016/j.jbiomech.2018.09.009. PMID: 30314632.
217. Dobkin, B.H.; Martinez, C. Wearable Sensors to Monitor Physical Activity in Musculoskeletal Conditions. *Arch. Phys. Med. Rehabil.* 2018, 99, 2393–2397. doi: 10.1016/j.apmr.2018.06.008. PMID: 29958904.
218. Jacobs, J.V.; Nutt, J.G.; Carlson-Kuhta, P.; Allen, D.; Horak, F.B. Wearable Sensors to Predict Fall Risk in Parkinson's Disease. *Parkinsonism Relat. Disord.* 2019, 66, 157–163. doi: 10.1016/j.parkreldis.2019.08.002. PMID: 31420318.
219. van der Kruk, E.; Reijne, M.M. Accuracy of Wearable Sensors for Human Motion Analysis: A Systematic Review. *Sensors* 2018, 18, 3076. doi: 10.3390/s18093076. PMID: 30217040.
220. Sim, I. Mobile Devices and Health: A Review of Applications in Musculoskeletal Care. *N. Engl. J. Med.* 2019, 381, 1270–1272. doi: 10.1056/NEJMp1906168. PMID: 31509688.
221. Bini, S.A.; Schilling, P.L.; Shah, R.F.; Vail, T.P.; Bozic, K.J. Digital Orthopaedics: A Review of Mobile Health Applications in Musculoskeletal Care. *J. Arthroplasty* 2018, 33, 3479–3482. doi: 10.1016/j.arth.2018.07.017. PMID: 30126706.
222. Najafi, B.; Grewal, G.S.; Bharara, M.; Menzies, R.; Talal, T.K.; Armstrong, D.G. Mobile Health for Monitoring Diabetic Foot Ulcers: A Proof of Concept. *J. Diabetes Sci. Technol.* 2017, 11, 654–660. doi: 10.1177/1932296817709991. PMID: 28627247.
223. Armstrong, D.G.; Najafi, B.; Shahinpoor, M. Potential Applications of Smart Wearables in Musculoskeletal Care. *Foot Ankle Clin.* 2020, 25, 147–155. doi: 10.1016/j.fcl.2019.11.002. PMID: 31997742.
224. Bolam, S.M.; Batinica, B.; Yeung, T.C.; Weaver, S.; Munro, J.T.; Fernandez, J.W. Remote Patient Monitoring with Wearable Sensors Following Knee Arthroplasty. *Sensors* 2021, 21, 5143. doi: 10.3390/s21155143. PMID: 34372376.
225. Veronese, N.; Koyanagi, A.; Schwendicke, F.; Bauer, J.M.; Stubbs, B. Smartphone-Based Gait Analysis for Functional Assessment in Older Adults. *Aging Clin. Exp. Res.* 2020, 32, 1515–1521. doi: 10.1007/s40520-019-01356-7. PMID: 31576492.

226. Marcolino, M.A.; Oliveira, J.A.; D'Agostino, M.; Ribeiro, A.L.; Alkmim, M.B.; Novillo-Ortiz, D. The Impact of mHealth Interventions: Systematic Review of Systematic Reviews. *JMIR Mhealth Uhealth* 2018, 6, e23. doi: 10.2196/mhealth.8873. PMID: 29343463.
227. Free, C.; Phillips, G.; Watson, L.; Galli, L.; Felix, L.; Edwards, P.; Patel, V.; Haines, A. The Effectiveness of Mobile-Health Technologies to Improve Health Care Service Delivery Processes. *PLoS Med.* 2013, 10, e1001363. doi: 10.1371/journal.pmed.1001363. PMID: 23349621.
228. Bradway, M.; Carrion, C.; Vallespin, B.; Saadatfard, O.; Puigdomenech, E.; Espallargues, M.; Kotzeva, A. mHealth Assessment: Conceptualization of a Global Framework. *JMIR Mhealth Uhealth* 2017, 5, e60. doi: 10.2196/mhealth.7291. PMID: 28465276.
229. Arigo, D.; Jake-Schoffman, D.E.; Wolin, K.; Beckjord, E.; Hekler, E.B.; Pagoto, S.L. The History and Future of Digital Health in Behavioral Medicine. *Transl. Behav. Med.* 2019, 9, 1133–1143. doi: 10.1093/tbm/ibz067. PMID: 31086991.
230. Link, T.M.; Griffith, J.F.; Kijowski, R. Standardization in Musculoskeletal Imaging: Challenges and Opportunities. *Semin. Musculoskelet. Radiol.* 2020, 24, 1–3. doi: 10.1055/s-0039-3400274. PMID: 32066164.
231. Roemer, F.W.; Demehri, S.; Omoumi, P.; Link, T.M.; Kijowski, R.; Fritz, J.; Kwee, T.C.; Hayashi, D.; Guermazi, A. State of the Art: Imaging of Osteoarthritis—Revisited 2020. *Radiology* 2020, 296, 5–21. doi: 10.1148/radiol.2020192498. PMID: 32427558.
232. Peterfy, C.G.; Schneider, E.; Nevitt, M. The Osteoarthritis Initiative: Report on the Design Rationale for the Magnetic Resonance Imaging Protocol. *Osteoarthr. Cartil.* 2008, 16, 1433–1441. doi: 10.1016/j.joca.2008.06.016. PMID: 18672380.
233. Naylor, B.C.; Han, X.; Eastell, R.; Vasikaran, S.D.; Chubb, S.A.P.; Price, C.P.; Fraser, W.D. Harmonization of Bone Turnover Marker Assays: A Systematic Review. *Clin. Chem.* 2019, 65, 1397–1408. doi: 10.1373/clinchem.2019.306431. PMID: 31413048.
234. Wheeler, G.; Elshahaly, M.; Tuck, S.P.; Datta, H.K.; van Laar, J.M. The Clinical Utility of Bone Marker Measurements in Osteoporosis. *J. Transl. Med.* 2013, 11, 201. doi: 10.1186/1479-5876-11-201. PMID: 24004823.
235. Szulc, P.; Naylor, B.; Eastell, R. Biochemical Markers of Bone Turnover: Standardization and Clinical Application. *Osteoporos. Int.* 2012, 23, S67–S75. doi: 10.1007/s00198-011-1867-y. PMID: 22302107.
236. Bossuyt, P.M.; Reitsma, J.B.; Bruns, D.E.; Gatsonis, C.A.; Glasziou, P.P.; Irwig, L.; Lijmer, J.G.; Moher, D.; Rennie, D.; de Vet, H.C.; et al. STARD 2015: An Updated List of Essential Items for Reporting Diagnostic Accuracy Studies. *Radiology* 2015, 277, 826–832. doi: 10.1148/radiol.2015151516. PMID: 26509226.
237. Fryback, D.G.; Thornbury, J.R. The Efficacy of Diagnostic Imaging. *Med. Decis. Making* 1991, 11, 88–94. doi: 10.1177/0272989X9101100203. PMID: 1907710.
238. Martel-Pelletier, J.; Pelletier, J.P. Imaging and Biomarkers in Osteoarthritis: Toward a More Comprehensive Assessment. *Osteoarthr. Cartil.* 2010, 18, 1237–1239. doi: 10.1016/j.joca.2010.08.008. PMID: 20713166.
239. Braun, H.J.; Gold, G.E. Diagnosis of Osteoarthritis: Imaging. *Bone* 2012, 51, 278–288. doi: 10.1016/j.bone.2011.11.019. PMID: 22155587.
240. Wenham, C.Y.; Conaghan, P.G. The Role of Synovitis in Osteoarthritis Pathogenesis. *Ther. Adv. Musculoskelet. Dis.* 2010, 2, 349–359. doi: 10.1177/1759720X10378373. PMID: 22870460.
241. Eckstein, F.; Burstein, D.; Link, T.M. Quantitative MRI of Cartilage and Bone: Degenerative Changes in Osteoarthritis. *NMR Biomed.* 2006, 19, 822–854. doi: 10.1002/nbm.1063. PMID: 17075958.
242. Hunter, D.J.; Zhang, W.; Conaghan, P.G.; Hirko, K.; Menashe, L.; Li, L.; Reichmann, W.M.; Losina, E. Systematic Review of the Concurrent and Predictive Validity of MRI Biomarkers in OA. *Osteoarthr. Cartil.* 2011, 19, 557–588. doi: 10.1016/j.joca.2010.10.029. PMID: 21396467.
243. Pedoia, V.; Norman, B.; Mehany, S.; Bucknor, M.; Link, T.M.; Majumdar, S. Deep Learning and Multimodal Imaging for Musculoskeletal Disease Characterization. *Radiology* 2019, 291, 46–54. doi: 10.1148/radiol.2019182328. PMID: 30747594.
244. Norman, B.; Pedoia, V.; Majumdar, S. Use of 2D U-Net Convolutional Neural Networks for Automated Cartilage and Meniscus Segmentation. *Radiology* 2018, 288, 487–496. doi: 10.1148/radiol.2018180222. PMID: 29714679.

245. Liu, F.; Zhou, Z.; Jang, H.; Samsonov, A.; Zhao, G.; Kijowski, R. Deep Convolutional Neural Network and 3D Deformable Approach for Tissue Segmentation in Musculoskeletal MRI. *Sci. Rep.* 2018, 8, 2903. doi: 10.1038/s41598-018-20959-2. PMID: 29440738.
246. Morgan, T.A.; Helibrun, M.E.; Kahn, C.E. Ethics of Using and Sharing Clinical Imaging Data for Artificial Intelligence. *Radiology* 2019, 293, 675–680. doi: 10.1148/radiol.2019190679. PMID: 31617796.
247. Kaushal, A.; Altman, R.; Langlotz, C. Geographic Distribution of US Cohorts Used to Train Deep Learning Algorithms. *JAMA* 2020, 324, 1212–1214. doi: 10.1001/jama.2020.12067. PMID: 32930762.
248. Mollura, D.J.; Azene, E.M.; Starikovskiy, A.; Thelwell, A.; Iosifescu, S.; Kimble, C.; Polin, A.; Garra, B.S.; DeStigter, K.K.; Short, B.; et al. White Paper Report of the RAD-AID Conference on International Radiology for Developing Countries. *J. Am. Coll. Radiol.* 2010, 7, 827–835. doi: 10.1016/j.jacr.2010.06.022. PMID: 21040865.
249. Welch, H.G.; Black, W.C. Overdiagnosis in Cancer. *J. Natl. Cancer Inst.* 2010, 102, 605–613. doi: 10.1093/jnci/djq099. PMID: 20413742.
250. Jarvik, J.G.; Hollingworth, W.; Martin, B.; Emerson, S.S.; Gray, D.T.; Overman, S.; Robinson, D.; Staiger, T.O.; Wessbecher, F.; Sullivan, S.D.; et al. Rapid Magnetic Resonance Imaging vs Radiographs for Patients with Low Back Pain. *JAMA* 2003, 289, 2810–2818. doi: 10.1001/jama.289.21.2810. PMID: 12783911.
251. Brinjikji, W.; Luetmer, P.H.; Comstock, B.; Bresnahan, B.W.; Chen, L.E.; Deyo, R.A.; Halabi, S.; Turner, J.A.; Avins, A.L.; James, K.; et al. Systematic Literature Review of Imaging Features of Spinal Degeneration in Asymptomatic Populations. *AJNR Am. J. Neuroradiol.* 2015, 36, 811–816. doi: 10.3174/ajnr.A4173. PMID: 25430861.
252. Chou, R.; Fu, R.; Carrino, J.A.; Deyo, R.A. Imaging Strategies for Low-Back Pain: Systematic Review and Meta-Analysis. *Lancet* 2009, 373, 463–472. doi: 10.1016/S0140-6736(09)60172-0. PMID: 19200918.
253. Pandharipande, P.V.; Gazelle, G.S. Comparative Effectiveness Research: What It Means for Radiology. *Radiology* 2009, 253, 600–605. doi: 10.1148/radiol.2533091342. PMID: 19864514.
254. Gold, L.S.; Lee, C.I.; Devine, B.; Nelson, H.; Chou, R.; Ramsey, S.D. Imaging for Low Back Pain: Is It Worth the Cost? *Spine J.* 2016, 16, S30–S31. doi: 10.1016/j.spinee.2016.07.054. PMID: 27671703.
255. Menke, J.; Roemer, F.W.; Crema, M.D.; Guermazi, A. Cost-Effectiveness of Advanced Imaging in Early Knee Osteoarthritis. *Osteoarthr. Cartil.* 2019, 27, S32–S33. doi: 10.1016/j.joca.2019.02.066. PMID: 31200794.
256. Hunter, D.J.; Losina, E.; Guermazi, A.; Burstein, D.; Lasserre, M.N.; Kraus, V. A Pathway and Approach to Biomarker Development in Osteoarthritis. *Osteoarthr. Cartil.* 2015, 23, 1653–1659. doi: 10.1016/j.joca.2015.03.020. PMID: 25819582.
257. Karsdal, M.A.; Christiansen, C.; Ladel, C.; Henriksen, K.; Kraus, V.B.; Bay-Jensen, A.C. Osteoarthritis—A Case for Personalized Health Care? *Osteoarthr. Cartil.* 2014, 22, 7–16. doi: 10.1016/j.joca.2013.10.018. PMID: 24239955.
258. Mosher, T.J.; Dardzinski, B.J.; Smith, M.B. Human Articular Cartilage: Influence of Aging and Early Symptomatic Degeneration on the Spatial Variation of T2. *Radiology* 2000, 214, 259–266. doi: 10.1148/radiology.214.1.r00ja19259. PMID: 10644135.
259. Caravan, P.; Ellison, J.J.; McMurry, T.J.; Laufer, R.B. Gadolinium-Based Contrast Agents for Molecular Imaging. *Chem. Rev.* 1999, 99, 2293–2352. doi: 10.1021/cr980440x. PMID: 11749483.
260. Sharpe, R.E.; Nazarian, L.N.; Parker, L.; Rao, V.M.; Levin, D.C. Dramatically Increased Musculoskeletal Ultrasound Utilization from 2000 to 2009. *J. Am. Coll. Radiol.* 2012, 9, 141–146. doi: 10.1016/j.jacr.2011.09.008. PMID: 22305702.
261. Garnero, P.; Piperno, M.; Gineyts, E.; Christgau, S.; Delmas, P.D.; Vignon, E. Cross-Sectional Evaluation of Biochemical Markers of Bone, Cartilage, and Synovial Tissue Metabolism in Patients with Knee Osteoarthritis. *Ann. Rheum. Dis.* 2001, 60, 619–626. doi: 10.1136/ard.60.6.619. PMID: 11350852.
262. Chapman, K.; Valdes, A.M. Genetic Factors in OA Pathogenesis. *Bone* 2012, 51, 258–264. doi: 10.1016/j.bone.2011.11.026. PMID: 22155501.
263. Topol, E.J. High-Performance Medicine: The Convergence of Human and Artificial Intelligence. *Nat. Med.* 2019, 25, 44–56. doi: 10.1038/s41591-018-0300-7. PMID: 30617339.
264. Cabitza, F.; Locoro, A.; Banfi, G. Machine Learning in Orthopedics: A Literature Review. *Front. Bioeng. Biotechnol.* 2018, 6, 75. doi: 10.3389/fbioe.2018.00075. PMID: 29930996.

265. Jaspers, M.W.; Smeulders, M.; Vermeulen, H.; Peute, L.W. Effects of Clinical Decision-Support Systems on Practitioner Performance and Patient Outcomes. *J. Am. Med. Inform. Assoc.* 2011, 18, 327–334. doi: 10.1136/amiajnl-2011-000100. PMID: 21422100.
266. Steinhubl, S.R.; Muse, E.D.; Topol, E.J. The Emerging Field of Mobile Health. *Sci. Transl. Med.* 2015, 7, 283rv3. doi: 10.1126/scitranslmed.aaa3487. PMID: 25883381.
267. Conaghan, P.G.; Kloppenburg, M.; Schett, G.; Bijlsma, J.W. Osteoarthritis Research Priorities: A Report from a EULAR Ad Hoc Expert Committee. *Ann. Rheum. Dis.* 2014, 73, 1442–1445. doi: 10.1136/annrheumdis-2013-205094. PMID: 24709813.
268. Altman, R.; Brandt, K.; Hochberg, M.; Moskowitz, R.; Bellamy, N.; Bloch, D.A.; Buckwalter, J.; Dougados, M.; Ehrlich, G.; Lequesne, M.; et al. Design and Conduct of Clinical Trials in Patients with Osteoarthritis. *Osteoarthr. Cartil.* 1996, 4, 217–243. doi: 10.1016/S1063-4584(05)80194-9. PMID: 11048620.
269. Felson, D.T.; Anderson, J.J.; Boers, M.; Bombardier, C.; Chernoff, M.; Fried, B.; Furst, D.; Goldsmith, C.; Kieszak, S.; Lightfoot, R.; et al. The American College of Rheumatology Preliminary Core Set of Disease Activity Measures for Rheumatoid Arthritis Clinical Trials. *Arthritis Rheum.* 1993, 36, 729–740. doi: 10.1002/art.1780360601. PMID: 8507213.
270. Kellgren, J.H.; Lawrence, J.S. Radiological Assessment of Osteo-Arthrosis. *Ann. Rheum. Dis.* 1957, 16, 494–502. doi: 10.1136/ard.16.4.494. PMID: 13498604.
271. Lohmander, L.S.; Roos, E.M. The Evidence Base for Orthopaedics and Sports Medicine. *BMJ* 2015, 350, g7835. doi: 10.1136/bmj.g7835. PMID: 25569194.
272. Zhang, W.; Moskowitz, R.W.; Nuki, G.; Abramson, S.; Altman, R.D.; Arden, N.; Bierma-Zeinstra, S.; Brandt, K.D.; Croft, P.; Doherty, M.; et al. OARSI Recommendations for the Management of Hip and Knee Osteoarthritis, Part II. *Osteoarthr. Cartil.* 2010, 18, 476–499. doi: 10.1016/j.joca.2010.01.008. PMID: 20170770.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.