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ARTIFICIAL INTELLIGENCE-DRIVEN BIOMECHANICAL MODELING AND PHYSICS-BASED ANALYSIS FOR EARLY PREDICTION OF SPINE AND JOINT DEGENERATION

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ABSTRACT
Degeneration of spine and joints constitutes one of the most prevalent causes of chronic pain, disabilities, and deteriorating quality of life around the world. Traditional methods of diagnosis usually diagnose degeneration only after considerable structural damage has happened, making it difficult for early intervention. The recent developments in artificial intelligence (AI), computational biomechanics, and digital health technologies provide promising capabilities in predicting and managing musculoskeletal diseases at an early stage. In this paper, we explore the use of AI-enabled analytics in combination with physics-based models of biomechanics to predict spine and joint degeneration. We describe various computational methods such as finite element analysis, musculoskeletal simulation, multibody dynamics, and patient-specific biomechanical modeling along with machine learning and deep learning methods. We focus particularly on hybrid AI-biomechanics approaches, physics-informed neural networks, multimodal fusion and digital twins using imaging, biomechanical, clinical and sensor data. Clinical applications such as degeneration prediction, surgery planning, monitoring of rehabilitation and personalized treatments are also explored. Additionally, the current challenges in data availability, model validation, interpretability, computational cost and clinical translation are mentioned. Lastly, the future directions include physics-informed foundation models, real-time digital twins, federated learning and autonomous decision-making systems. Collectively, these advances have the potential to transform musculoskeletal healthcare from reactive treatment toward predictive, preventive, and precision medicine.

KEYWORDS: Artificial Intelligence, Biomechanical Modeling, Digital Twins, Spine Degeneration, Osteoarthritis Prediction.

1. INTRODUCTION

MSDs include spine degeneration and osteoarthritis of major joints and are major causes of chronic pain, disability and poor quality of life globally. Osteo-changes of the intervertebral discs, vertebral end plates, articular cartilage, subchondral bone, and connective tissues may gradually occur without being noticed. Thus, the conventional diagnostic approaches including clinical assessment based on symptoms, magnetic resonance imaging (MRI), and radiography usually fail to reveal any degenerative signs until the disease reaches an advanced stage when treatment makes regeneration less likely [1]. In this regard, the need for predictive and preventive strategies aimed at detecting biomechanical dysfunctions as well as the development of tissue alterations causing degeneration before their clinically apparent manifestations occurs.

The domain of biomedical research and health care is being continually transformed due to the latest advances in artificial intelligence (AI) which have enabled data analysis, pattern recognition, predictive modeling, and decision support systems [2,3,4]. There has been significant potential for AI-powered approaches in various medical applications, such as disease diagnosis, image analysis, risk assessment, and treatment planning. In cardiovascular medicine, AI-based predictive technologies have been used successfully to incorporate large-scale, heterogeneous clinical and patient datasets, and to uncover complex nonlinear relationships that are hard to identify using traditional statistical methods [2,5]. In the same manner, the use of data-driven optimization frameworks using AI technology has also led to improved predictive performance in biomedical engineering applications, highlighting the flexibility and scalability capabilities of AI in the field of medical research. The data-driven optimization frameworks can be implemented through the use of AI, which has been proven to help improve the predictive performance in biomedical engineering applications, making AI more versatile and scalable in the field of medical research [6]. In addition, AI-based biomimetics involving biological processes is leading to the development of self-learning computational systems.

Parallel to these developments, biomechanics has emerged as a powerful discipline in unraveling the mechanics of biological tissues and organ systems in physiological as well as pathological scenarios [7]. The application of physics-based computational approaches like finite element analysis (FEA), has become absolutely necessary in the understanding of stresses, strains, tissue deformation, and failure modes. Finite element models provide simulation of individualized anatomical structures and mechanistic insights into disease progression, treatment planning, and outcomes [8]. Recent computational studies have also revealed that biomechanics is of fundamental importance in understanding the mechanics of tissue, fractures, and structural degradation in various biological systems [9]. These developments have made it possible for biomechanical modeling to be an integral part of precision medicine.

The application of artificial intelligence and computational biomechanics is providing new opportunities for predicting the onset of musculoskeletal degeneration. While biomechanical models allow a deeper understanding of the mechanism and physical accuracy, they may still be extremely time-consuming to calibrate and demand expertise as well as high computational power [10]. In contrast, purely data-driven AI models enable quick predictions and can scale easily, yet are often hard to interpret and do not provide mechanistic insights. Combining machine learning techniques and physics-driven biomechanical simulation becomes a new promising direction with both good predictive abilities and biomechanical accuracy [11,12]. This combination allows using multimodal information obtained through medical imaging, clinical examination, gait analysis, wearable sensors, and biomechanical simulations to detect degenerative changes much earlier than the changes would be visible in the radiological images.

This paradigm shift has been further accelerated by the swift advancement of digital health technologies. Every day, digital therapeutics, healthcare systems coupled with tele-rehabilitation, wearable monitoring devices and remote health platforms collect and transmit massive amounts of biomechanical and physiological data that can be leveraged to predict and manage disease in a personalised way [13]. At the same time, digital twin technology has emerged as a transformative concept, one that has digital replicas of physical systems that dynamically incorporate real-time data, computational simulations and predictive analysis. In recent years, digital twins have been brought up as a valuable tool for applications in the healthcare, medical product development, rehabilitation, and treatment optimization for individual patients [14,15]. Furthermore, as the capability of biomaterials development, regenerative medicine, and high precision additive manufacturing has improved, patient specific anatomical models are becoming more and more complex and realistic to facilitate a biomechanical simulation with greater reality and relevance [16].

However, despite all the advantages and promising prospects of applying AI-based biomechanical systems for diagnostics and treatment purposes, there is an array of obstacles that prevent the widespread implementation of the technology. The main barriers to translation include data heterogeneity, insufficient availability of longitudinal data, the necessity of validating the proposed models, cybersecurity problems, ethical concerns, and regulatory limitations [17]. Furthermore, the use of several types of data for multimodal purposes requires very sophisticated computational power to provide scalability, privacy and interoperability. It is expected that some of the above mentioned problems will be addressed by new technological approaches such as Industry 6.0, intelligent manufacturing, federated learning, edge intelligence and next generation foundation models that are able to increase the robustness and generalizability of the predictive health care systems [18].

From this perspective, the novel approach involving the combination of artificial intelligence and biomechanical modeling on the basis of physics and digital twins becomes a revolution in the early detection of spine and joints' degeneration. Such an approach will enable a comprehensive approach to the treatment of musculoskeletal disorders through the combination of mechanistic principles and predictive analysis, thus turning musculoskeletal medicine into a prevention-oriented one rather than mere disease management. The goals of the review are the following:

1. To analyze AI methods that aid in early prediction of spine and joint degeneration
2. To analyze physics-based methods used in biomechanics for risk assessment in musculoskeletal systems
3. To analyze the digital twin approach and AI-biomechanics hybrid models for precision musculoskeletal healthcare

2. Biological and Biomechanical Basis of Degeneration

2.1 Pathophysiology of Intervertebral Disc Degeneration

Disc Degeneration is a significant cause of Chronic Low Back Pain and involves degenerative changes occurring in terms of structure and biochemistry in the nucleus pulposus, annulus fibrosus, and vertebral endplates. The early stages of disc degeneration involve disc dehydration through the loss of proteoglycans. These changes cause decreased shock absorbing abilities of the disc and changes in load bearing capabilities [19]. Calcification of the endplate causes problems in the delivery of nutrients and increases cellular degeneration.

2.2 Biomechanics of Osteoarthritis

Osteoarthritis (OA) is a complex disease process that affects joints via destruction of the cartilage matrix, subchondral bone changes, and inflammation of the synovium. Mechanical overloading and aging compromise the stability of the extracellular matrix, causing degradation of the collagen and proteoglycan content of the joint cartilage [20,21]. At the same time, bone remodeling abnormalities result in bone sclerosis, thickening of the trabeculae, and osteophyte growth. The inflammatory factors released from the synovium enhance the process of joint destruction.

2.3 Mechanobiology and Tissue Adaptation

Mechanobiology refers to the effect of mechanical cues on cell behavior and tissue remodeling. As per Wolff's Law, musculoskeletal tissues structurally adapt to their mechanical environment to retain their functionality. Mechanotransduction of the mechanical cues into biochemical signals controls matrix production, inflammation, and cell survival [22,23]. Excessive or abnormal loading may alter the regulation processes, resulting in oxidative stress, matrix breakdown, apoptosis, and inflammation. Therefore, pathologic mechanical environments become the main contributors to musculoskeletal disorders.

2.4 Multiscale Nature of Musculoskeletal Degeneration

Degeneration of the musculoskeletal system is a multilevel process characterized by interlinked alterations at the cellular, tissue, organ, and organism levels. Altered mechanical stimulation results in changes in gene expression, metabolism, and inflammation processes at the cellular level. The resulting changes become evident at the tissue level through collagen disruption, proteoglycan loss, and accumulation of micro-damage (Figure 1) (Table 1). Organ-level degeneration impacts the biomechanics of discs, cartilage, ligaments, tendons, and joints through modification of their stress patterns and movements [24]. Postural and gait compensation affect organismal mechanics as well.

Table 1: Biological Basis of Musculoskeletal Degeneration

Subsection	Key Features	References
IVDD	Dehydration, endplate changes, instability	[19,20]
Osteoarthritis	Cartilage loss, bone remodeling, inflammation	[21]
Mechanobiology	Wolff's law, mechanotransduction, overloading	[22,23]
Multiscale Degeneration	Cellular, tissue, organ, whole-body changes	[24]

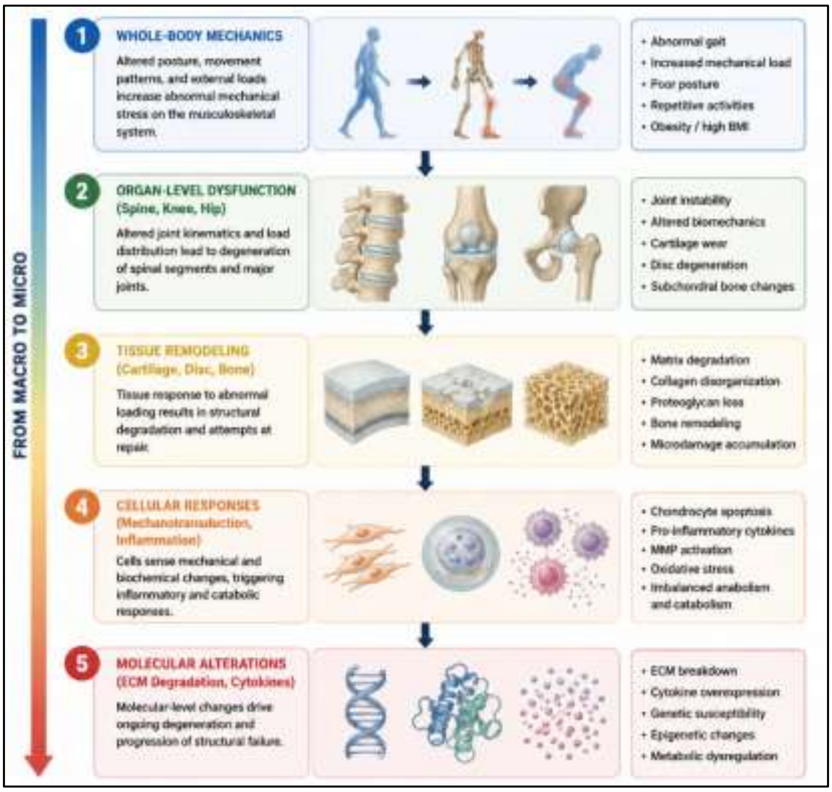

Figure 1: Biological and Biomechanical Basis of Degeneration

3. Computational Biomechanical Modeling Approaches

3.1 Finite Element Modeling (FEM)

Finite element modeling (FEM) is one of the most popular computational methods used to study the biomechanics of musculoskeletal tissues. FEM allows for the stress distribution, strain patterns and tissue deformations to be analysed in detail, in physiological and pathological loading conditions, by dividing anatomical structures into smaller elements. These include assessment of intervertebral disc degeneration; progression of OA, implant performance and spinal instability [25]. While FEM offers very accurate information regarding the tissue, the use of the technique in patients can be hampered by significant computational demands and problems with patient-specific parameter estimation and model validation.

3.2 Musculoskeletal Modeling

Musculoskeletal modeling is the study of the function of bones, muscles, tendons, ligaments, and joints through simulation to estimate the internal forces and movements. Various platforms, such as OpenSim, are available which can be used to build models specific to a particular subject that can be used to predict muscle activations, joint moments, and joint reaction forces [26]. These models are useful in evaluating biomechanics of gait, posture, and loading conditions during motion that may lead to musculoskeletal disorders. Musculoskeletal models combine motion capture and biomechanical data to afford important insights into the process of disease progression, rehabilitation outcomes, and strategies for optimizing treatment.

3.3 Multibody Dynamic Simulations

A multibody dynamics simulation defines the musculoskeletal system as a combination of rigid or deformable bodies which interact with each other by means of joint or constraint connections. With such a modeling approach, it is possible to quickly analyze the complexities of human movements and force transmission during activities of daily living. One can say that the multibody simulations have the advantage of being faster than FEMs while still providing realistic models of whole body motion [27,28]. In addition, multibody simulation models are commonly used to predict human motion, compensate movements and estimate biomechanical risk factors for degeneration.

3.4 Patient-Specific Biomechanical Models

Biomechanical models are patient-specific, using patient anatomy and functional information to increase the accuracy of predictions and support personalized medicine. With the help of modern imaging technologies such as magnetic resonance imaging (MRI) and computed tomography (CT), geometrical shapes of tissues such as cartilage, intervertebral discs, ligaments, and bones can be modeled (see Table 2) [29]. These models also include individual loads that are dependent on body mass, patient posture, patient activities and gait characteristics. These models account for patient-specific biomechanics and give more accurate predictions regarding degenerative risk, efficacy of treatments and surgical planning. The possibility of their integration with wearables and artificial intelligence brings about the development of musculoskeletal digital twins.

Table 2: Comparison of Major Computational Biomechanical Modeling Approaches

Model Type	Primary Output	Advantage	Limitation	Application	References
FEM	Stress/Strain	High accuracy	High computational cost	Disc degeneration	[25]
Musculoskeletal Modeling	Joint Loads	Whole-body analysis	Simplified tissue mechanics	Gait analysis	[26]
Multibody Dynamics	Kinematics	Fast simulation	Limited tissue detail	Functional assessment	[27,28]
Patient-Specific Models	Personalized Prediction	Precision medicine	Data intensive	Surgical planning	[29]

4.Artificial Intelligence in Musculoskeletal Health

Artificial intelligence (AI) is a powerful technology in the field of musculoskeletal medicine today, allowing us to offer innovative methods for prediction, diagnosis, treatment, and management of patients with musculoskeletal diseases. Due to the increasing availability of large databases of clinical, medical image, EHR data, and biomechanical information, machine learning and deep learning technologies are becoming increasingly popular in addressing complicated cases of musculoskeletal disorders [30,31]. AI's capacity to recognize the intricate features of diseases that could possibly go unnoticed during routine clinical examinations can also assist in the early diagnosis of degenerative diseases and the introduction of precision medicine treatments. The application of artificial intelligence in the management of low back pain, neck pathologies, osteoarthritis, rheumatic diseases, and sport-related injuries has been proven to be clinically relevant in musculoskeletal medicine.

Random forest, Extreme Gradient Boosting (XGBoost), and Support Vector Machines (SVMs) are among the machine learning methods that have been used extensively in the classification of diseases, as well as predicting the risks and outcomes. These models can detect large multidimensional data sets and capture the nonlinear correlations among the demographic, clinical, imaging, and biomechanical factors (Figure 2) [32]. Nonetheless, deep learning networks have made significant contributions to the improvement of predictive power in musculoskeletal applications in recent years. With the capacity to automatically derive hierarchical features from MRI, CT, radiographic and ultrasonographic images, the Convolutional Neural Networks (CNNs) emerged as the most prominent technique for image analysis [33,34]. With respect to the complexity of the spatiotemporal relations in musculoskeletal systems, the rising deep learning architectures, including Transformer and Graph Neural Networks (GNNs) create new possibilities for modeling the degenerative pathway and predicting the disease progression.

Another effective application in musculoskeletal health is medical imaging. With respect to MRI imaging, artificial intelligence can facilitate the grading of intervertebral disc degeneration, cartilage assessment, tissue segmentation and structure characterization [35], while CT imaging can facilitate the determination of bone morphology, vertebral status and skeletal anomalies. Additionally, AI-driven radiographic analysis is found to be very accurate in automated severity grading of OA and spinal degeneration, thereby increasing the consistency of diagnostics and reducing the variability of interpretations [35]. To gain the trust of clinicians, explainable AI algorithms like SHAP, LIME and attention maps have been developed in order to provide explanations to model predictions. Furthermore, the creation of foundation models, multimodal learning approaches, and vision-language models expands the capabilities of AI by moving beyond mono-modal tasks to include imaging, clinical, biomechanical and textual information in one predictive model [36]. Altogether, these technologies create a comprehensive AI-based ecosystem capable of aiding early diagnostics, individualized treatment plan development and prediction of the spine and joint degeneration.

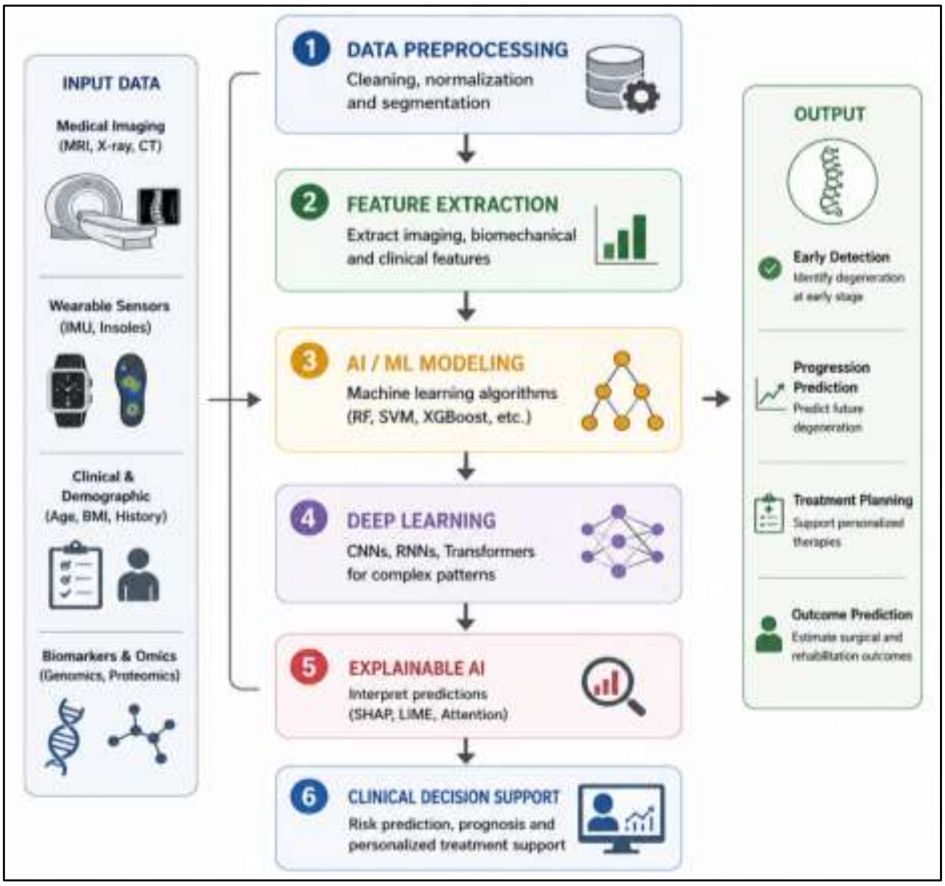

Figure 2: Artificial Intelligence in Musculoskeletal Health

5. Application of AI to Physics-Based Biomechanical Modeling

Integration of AI with Physics-Based Biomechanical Modeling (PBM) represents an emerging approach to the problem of musculoskeletal prediction and degeneration. Although AI algorithms are able to find complex patterns within huge amounts of data, data-driven models can face problems with availability of sufficient amount of data, lack of transparency, and poor generalization to various patient groups [37]. Machine learning systems are "black-box" systems that provide perfect predictions, but no mechanistic understanding of why these predictions are correct. However, for musculoskeletal cases, where there is plenty of biological variability and biomechanics involved, it could be problematic to rely on AI alone.

In order to tackle the mentioned difficulties, hybrid approaches combining AI with biomechanics have been proposed in an attempt to incorporate the learning approaches with the classical concepts of biomechanics. The aforementioned approach incorporates machine learning techniques along with biophysical models of tissue mechanics, tissue loading, and functioning [38,39]. The idea behind mechanistic learning approaches is to allow AI techniques to learn not only based on observational data but also based on underlying physical laws, which will provide additional robustness and physiological plausibility.

Among the most important achievements in this area should be mentioned Physics-Informed Neural Networks (PINNs), in which equations and boundary conditions are incorporated into the learning process. Moreover, PINNs differ significantly from classic neural networks that are based only on a great deal of labeled data by using physical laws to guide the optimization process and thus improve the accuracy of prediction (see Table 3) [40,41,42]. Such models were successfully applied in biomechanics to analyze the deformation of tissues, estimate the stress and strain, fluid-structure interaction, and physiological system modeling. PINNs allow for reliable prediction of the results of experiments even when experimental data is scarce by incorporating biomechanical knowledge into the data-driven learning process.

The important advance has been the development of surrogate models in finite element simulations. While traditional finite element analysis models are difficult to implement and expensive, and seldom used for clinical practice in real time, they provide highly valuable biomechanical information [43]. The surrogate models are approximate models of finite element analysis outcomes produced by the use of neural networks and reduced order modeling techniques, being substantially cheaper to calculate. The surrogate models are capable of predicting stress distribution, tissue behavior, and vulnerability to degeneration in extremely fast time.

Notably, there is an increase in explainability and robustness of the models with the use of physical constraints. The use of a hybrid model guarantees that the results obtained are in line with existing biomechanical knowledge and thus provide much more explainable results compared to traditional black-box AI approaches [44]. It can be concluded that the combination of physics-based biomechanics with AI represents a significant breakthrough in the development of predictive models of spine and joint degeneration.

Table 3: Comparison Between AI-Only and Hybrid AI–Biomechanics Approaches

Feature	AI Only	Hybrid AI–Biomechanics	Key References
Interpretability	Low	High	[37,38]
Physical Consistency	Limited	Strong	[39]
Data Requirement	High	Moderate	[40]
Generalizability	Moderate	Better	[41,42]
Clinical Trust	Lower	Higher	[43]
Computational Cost	Low–Moderate	Moderate	[44]

6. Digital Twins for Spine and Joint Degeneration

6.1 Concept of Musculoskeletal Digital Twins

The musculoskeletal digital twin refers to the virtual model of a specific patient where there is a continuous integration of data related to the anatomy, physiology, biomechanics, and clinical aspects of that patient. As opposed to the conventional models, digital twins are regularly updated with new data collected from the patient in order to be able to make real-time prediction of the disease progression. In the context of musculoskeletal care, Digital Twins provide various possibilities for the personalization of diagnosis, treatment optimization and outcome prediction. They are particularly valuable in the treatment of chronic degenerative conditions of spine and joints [45], as they allow for individual simulations that cannot be done on humans.

6.2 Components of a Digital Twin

The musculoskeletal digital twin relies on the capability of being connected with different data sources and computational modules. Methods such as MRI and CT scanning can be applied to create a thorough reconstruction of bone structure, cartilages, tendons and discs. Biomechanical models demonstrate the loading of tissues, mechanics of joint functioning and dynamics of movements, while the sensors which are worn on the body will deliver data constantly related to the physiological side of movements [46]. AI prediction engines process all these multimodal data sets in order to find patterns of tissue degeneration and clinical outcomes predictions. All these elements are interconnected and form a continuously updating virtual model of musculoskeletal system functioning.

6.3 Spine Digital Twins

The application of digital twins is becoming more common within the realm of spinal health care. It is possible to use patient-specific spine models in order to perform simulations and understand the progress of diseases and the effect of therapy before implementing the treatment methods in practice [47]. There have been recent findings that digital twins can be used to predict intervertebral disc degeneration, vertebrae fractures, spinal deformity development, and surgical outcomes. The use of spine digital twins is extremely valuable for clinicians because these models combine biomechanical simulations and artificial intelligence in order to optimize personal treatment.

6.4 Joint Digital Twins

Joint digital twins have been increasingly used in the treatment of knee osteoarthritis, hip degeneration and other similar conditions. Joint digital twins make use of imaging-derived anatomical information, gait mechanics, clinical examination and sensor-based monitoring, which are then used to model the disease progression of individuals [48]. Digital twins will be able to predict cartilage degeneration, response to treatments, and assist in making joint clinical decisions in knee osteoarthritis. The same is being done for hip degeneration and planning of arthroplasty.

6.5 Current Challenges

Even though digital twins present great promise, there are some barriers which must be dealt with before digital twins become more widespread. The creation of an integrated and holistic data set from imaging systems, wearable devices, biomechanical modeling and electronic health records is difficult (Figure 3)[49, 50]. Furthermore, rigorous validation is needed in order to achieve accurate, reliable and repeatable predictions. Some of the other barriers to clinical implementation are regulatory clearance, issues with data privacy, cybersecurity threats, and ethics. In order for digital twins to become a commonplace method of personalized musculoskeletal healthcare, these barriers need to be addressed.

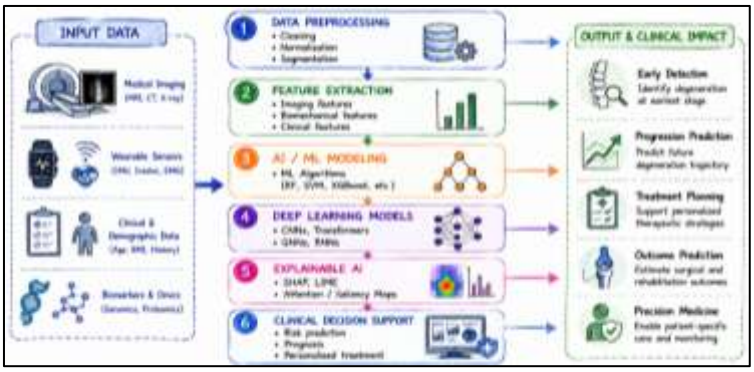

Figure 3: Digital Twins for Spine and Joint Degeneration

7. Multimodal Data Fusion for Early Prediction

7.1 Medical Imaging

Medical imaging is among the main components of multimodal prediction models of musculoskeletal degeneration. MRI is an advanced modality which allows obtaining highly detailed images of soft tissues, including intervertebral discs, cartilage, ligaments, and tendons and can help identify structural abnormalities in time [51,52]. CT is an effective method of imaging bone morphology, structure of vertebrae, and alignment of joints, while ultrasonography can be used to evaluate inflammation and soft tissue structures dynamically. This combination of imaging modalities increases the diagnostic accuracy and allows the complete assessment of structural abnormalities resulting from the disease.

7.2 Wearable Sensor Data

Wearable devices have the potential to provide continual information about the real world biomechanics along with imaging techniques. IMUs detect patterns of motion, angular velocity, and acceleration that are related to gait and posture. Plantar pressure distribution and load bearing are observed with the help of smart insoles, whereas kinematic analysis of joints can be obtained with the aid of motion capture systems [53,54,55]. The data gathered through the use of sensors can be used to detect abnormalities that can occur before structural changes.

7.3 Clinical and Demographic Data

Clinical and demographic variables are, however, significant predictors of degenerative conditions and can be used along with other variables in multimodal prediction models. Some of the major variables that have an impact on predisposition and progression of the disease are age, gender, body mass index (BMI), occupation, lifestyle-related factors, and medical history [56,57]. Genetic variability also exists in terms of risk for degeneration and response to therapy. Demographic and clinical information can be used together with imaging and biomechanical analysis to build a more complete picture of the patient and improve patient-specific prediction models.

7.4 Omics and Biomarkers

The utility of omics data in predicting diseases has been expanded with the latest advancements in high throughput technologies in biology. Latest advancements in the field of high throughput biological technologies have expanded the uses of omics data in disease prediction.Genomics provides insights into the molecular mechanisms and genetic susceptibility towards degeneration while the proteomics reveals the pattern of protein expression related to tissue remodeling and inflammation [58,59]. The use of metabolomics provides insight into metabolic alterations due to progression of the disease. All the above biomarker based approaches collectively assist in recognizing the pathological changes in the initial stages when there are no structural changes evident.

7.5 Fusion Architectures

The concept of multimodal data fusion techniques is to combine multiple information sources to form a single prediction model. The process of early fusion is applied in fusing multiple datasets at the input stage before modeling where one can learn multiple features from the different data sources. Late fusion: Increased robustness and flexibility due to combination of predictions that are separately computed from different data sources (see Table 4) [60,61,62]. Hybrid fusion techniques make use of both early and late fusion in an attempt to benefit from the strengths of the two approaches. Multimodal data fusion analysis of complex relationships among images, sensors, clinical and biomarker information is now possible using recent deep learning-based multimodal fusion techniques.

Table 4: Multimodal Datasets Used for Degeneration Prediction

Data Source	Examples	Clinical Relevance	References
MRI	Disc grading, cartilage assessment	Structural changes	[51,52,53]
CT	Bone morphology, alignment	Skeletal integrity	[54,55]
Wearables	IMUs, smart insoles	Functional assessment	[56,57]
Clinical Data	Age, BMI, history	Risk stratification	[58,59]
Omics	Genomics, proteomics	Molecular mechanisms	[60,61,62]

8. Clinical Applications and Case Studies

The management of musculoskeletal disorders using artificial intelligence (AI) and computational biomechanics is currently undergoing a radical shift. One of the most promising applications of AI involves the early diagnosis of intervertebral disc degeneration, a condition where AI algorithms analyze imaging biomarkers, biomechanics data, and individual risk factors for detecting early signs of intervertebral disc degeneration even before serious changes happen [63] (see Figure 4). Similarly, predictive models are utilized for predicting the progression of OA based on radiographic findings, gait biomechanics, clinical data, and individual data of patients.

Another one of these clinical applications is the prediction of surgical outcome. If used in combination, biomechanical simulation and machine learning models could help predict the degree of spinal stability post-surgery, the performance of the implant, functional recovery, and possibility of complications prior to surgery [64,65,66]. This predictive ability could be useful in the process of evidence-based treatment planning. Furthermore, with the use of artificial intelligence technology, the design of implants could be significantly improved due to the ability to model the stresses on the implant, its properties and interaction with tissue during loading of the spine.

Monitoring and rehabilitation through AI and biomechanics is another area where AI is becoming increasingly popular. Wearable sensors, mobile health and remote monitoring technologies make it possible to continuously monitor patients' movements, physical activity and recovery progress [67]. The data collected can be fed into machine learning algorithms which will detect any anomalies within the data which are normal during the recovery period [68]. These technologies will help with customized rehabilitation programs and improve patient compliance with the therapy. Continuous health monitoring outside the clinic environment is easily done using health apps and digital technologies [69].

One of the most promising ways to use AI-driven biodynamic modeling is the development of individualized therapy. Thanks to such a combination of medical imaging, simulations, clinical data, demographic data, and patient-reported outcomes, it is possible to develop individualized treatments depending on the condition of each patient. Moreover, it should be noted that the development of personalized treatments is additionally supported by the development of federated learning, predictive analytics, and AI-driven decision support systems, which make these personalized treatments more precise and comprehensive [70,71,72]. With their development and improvement, it is expected that they will bring a change in paradigms of treating spine and joint degeneration from the reactive one to proactive prevention and precision medicine of musculoskeletal system. Summarizing everything above, it is possible to say that the applications of AI-driven biodynamics in clinical research are very promising and valuable.

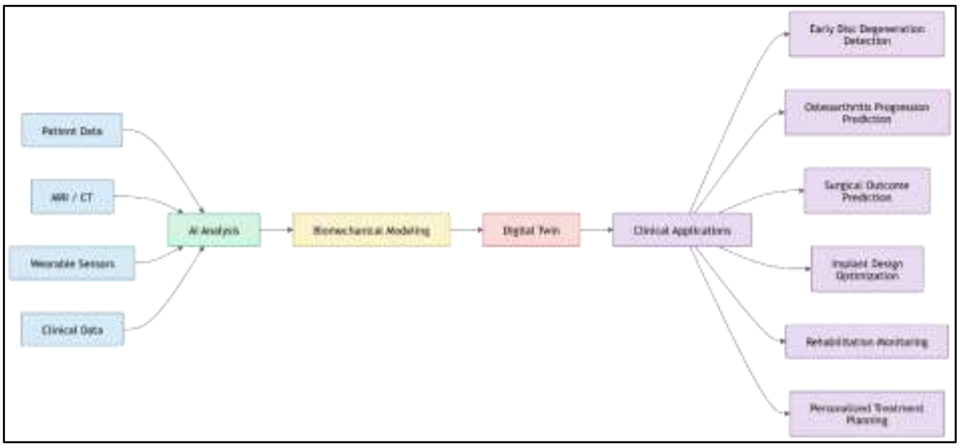

Figure 4: Clinical Workflow Integrating AI and Biomechanics

10. Challenges and research gaps in the present times.

While great strides have been made in artificial intelligence (AI), computational biomechanics, and digital twin technologies have been achieved, there remain a number of challenges in the way of their clinical use in musculoskeletal health care. A major constraint is the absence of big-scale longitudinal data sets that can track disease progression over longer time scales. Available studies are mostly based on cross-sectional or institution-specific data sets, meaning that predictive models are difficult to accurately predict long-term degeneration trajectories. Moreover, gathering biomechanical ground truth is challenging, as in vivo measurements of stresses, strains, and joint loading are often impractical and/or invasive. Many computational models rely on assumptions and indirect estimate that can cause uncertainty. Another significant challenge is computational complexity. High fidelity finite element and patient specific digital twins are very computational expensive and can not be used routinely in the clinic. Furthermore, numerous high-end AI models are black-box systems, making it difficult to understand them and thus limiting the trust placed in them by clinicians and the ability to pass regulatory testing. A rising need in the healthcare field for models that give interpretable predictions and mechanistic explanations for clinical recommendations has been observed.It is observed that the need for models providing interpretable predictions and mechanistic explanations of clinical recommendations is on the rise in healthcare. However, workflow integration problems, data privacy concerns, regulatory requirements and multidisciplinary expertise are further barriers to clinical adoption. Last but not least, there is no uniform reporting procedure, validation framework, benchmarking approach, or data sets, which can complicate the comparison of models across studies and generate reproducible evidence. Mitigating these challenges will be essential to the successful integration of AI-powered biomechanical innovations from the lab into everyday MSK treatment.

11. Future Directions

Artificial Intelligence (AI), Computational Biomechanics, and Digital Twins will impact musculoskeletal health care in the future. One of the trends includes the development of "physics-informed" foundation models which make use of large data learning, physics, and physiological constraints. The use of physical laws in such models helps to improve prediction, interpretability, and generalization abilities of the models as well as reduces the necessity of collecting large amounts of labeled data. Real-time biomechanical digital twins, which include updating of patient-specific models from medical images, wearable devices, and clinical examinations, are also among the main trends. They will help to monitor disease progression, responses to treatment, and functional recovery in real time and make early clinical decisions possible. Generative AI technology will also be widely used in creating synthetic patient data sets that solve the problem of the lack of data, increase the robustness of models, and provide patients' privacy when building algorithms. The last one is the paradigm of federated learning which allows training AI models in several institutions without sharing patients' sensitive data. This will increase dataset variability, reduce biases, and make predictive models externally valid.

Meanwhile, reinforcement learning algorithms can be used for adaptive optimization of the treatment process through learning from patients' reactions and adjustment of treatment regimes. They can improve planning of rehabilitation, surgical procedures, and treatment regimes for individual patients. Finally, the introduction of digital autonomous clinical decision support systems (C-DSS) based on various types of data, biomechanical simulations, digital twins, and predictive analytics can revolutionize the field of musculoskeletal medicine. Overall, these technologies will aid in transitioning from reactionary approach to disease treatment to proactive disease prevention and personalized diagnostics, resulting in the ability to diagnose diseases earlier and select the appropriate disease treatments.

12. CONCLUSIONS

The interaction of AI technology, computational biomechanics, multimodal data fusion, and digital twin technologies is transforming musculoskeletal healthcare. Studies conducted recently show that the use of artificial intelligence could help in the detection of spine and joints' degeneration in its early stages, as well as predict potential diseases. The combination of the knowledge of the biomechanics and application of machine learning techniques may be beneficial as an option of increased interpretability, physiology and accuracy compared to data-driven approaches. In addition to that, innovative technologies such as physics-informed neural networks, patient-specific digital twins and multimodal prediction models open the doors for the development of precision medicine of musculoskeletal disorders. Even though there are certain limitations, such as lack of data and difficulties with validation of the model, high computational cost, explainability, and clinical adoption problems, those challenges are constantly being solved. In the future, next generation of musculoskeletal digital twins with real-time sensing, explainable AI and personalized predictive analytics will enable a transformation of musculoskeletal healthcare from disease management into prevention and personalization approach.

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