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Review Article

Computational Modelling of Bone Remodelling: Integration of Finite Element Analysis, Machine Learning, and Mechanobiological Principles

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Bone Tissue Structure and Mechanobiological Principles

Bone tissue serves as the primary structural framework of the musculoskeletal system, comprising approximately 25% of protein content in mammals [1]. The remarkable mechanical properties of bone derive from its hierarchical structure, with collagen being the predominant protein component that provides tensile strength and flexibility [2]. Within bone microenvironments, specialized cells called osteoblasts, analogous to fibroblasts in other connective tissues, orchestrate the production and organization of the extracellular matrix components [3]. Osteoblasts secrete procollagen molecules that undergo extracellular processing to form mature collagen fibrils, which subsequently organize into larger fibres that establish the structural foundation for mineral deposition [4,5].

The biomechanical properties of bone tissue emerge from the precise spatial arrangement of collagen fibres, which align in response to mechanical loading patterns [6]. This alignment process involves a bidirectional communication between cells

and the surrounding matrix, wherein fibroblasts and osteoblasts simultaneously respond to and influence the orientation of collagen fibres [6,7]. This dynamic reorganization contributes significantly to the anisotropic mechanical behaviour observed in bone tissue across different anatomical locations. The mechanical performance of bone further depends on its viscoelastic properties, which allow for energy dissipation during loading and contribute to fracture resistance [8,9].

Bone tissue exhibits remarkable piezoelectric properties, enabling the conversion of mechanical stress into electrical potentials [10]. This electromechanical coupling plays a vital role in bone adaptation and remodelling processes, creating bioelectrical signals that influence cellular behaviour in response to mechanical loading [11]. The piezoelectric effect in bone derives primarily from the asymmetrical arrangement of collagen molecules and associated glycosaminoglycans, generating streaming potentials when fluid flows through the canalicular network during mechanical deformation [12]. These electrical signals contribute to the mechanosensory mechanisms that guide bone adaptation in response to functional demands [13].

Integrin-Mediated Cell-Matrix Interactions

The communication between bone cells and their surrounding extracellular matrix critically depends on specialized transmembrane receptors known as integrins [14]. These heterodimeric proteins facilitate bidirectional signalling across the cell membrane, allowing cells to sense and respond to the mechanical and biochemical properties of their microenvironment [15]. Integrins specifically bind to collagen through recognition sequences, establishing mechanical linkages that transmit forces between the extracellular matrix and the cytoskeleton. This mechanical coupling enables bone cells to detect deformations in the surrounding matrix and initiate appropriate cellular responses [16].

Integrin-mediated adhesion to collagen involves a complex process wherein integrin molecules transition from a folded, inactive conformation to an extended, active state upon binding to their ligands [17]. This conformational change facilitates the recruitment of various adapter proteins that link the integrin cytoplasmic domains to the actin cytoskeleton, establishing a continuous mechanical pathway for force transmission [18]. The resulting adhesion complexes not only provide structural support but also serve as signalling hubs that integrate mechanical and biochemical cues to regulate cellular behaviours such as proliferation, differentiation, and matrix production [19].

Recent investigations have demonstrated that knockout mice with combined ablation of collagen-binding integrins α1β1, α2β1, and α11β1 exhibit significant alterations in fibroblast function and matrix organization [20]. These triple knockout mice develop with mild alterations in skin mechanical resilience and show severely attenuated fibrotic responses, indicating the crucial role of integrin-collagen interactions in tissue remodelling and mechanical adaptation [21]. The impaired mechanotransduction observed in these models underscores the essential function of collagen-binding integrins in sensing mechanical forces and translating them into cellular responses that drive bone remodelling processes.

Mechanotransduction and Cell Cycle Regulation

Mechanical forces profoundly influence bone cell proliferation and differentiation through mechanotransduction pathways that convert physical stimuli into biochemical signals [22]. These pathways involve various mechanosensory, including integrin-based adhesion complexes, stretch-activated ion channels, and cytoskeletal components that detect and respond to mechanical deformation [23]. The resulting intracellular signalling cascades ultimately regulate gene expression patterns that determine cell fate and function within the bone microenvironment.

Cell cycle progression in bone-forming cells is tightly regulated by mechanical cues through mechanisms involving cyclin-dependent kinases (CDs) and their regulatory partners, cyclins. Mechanical stimulation activates signalling pathways that enhance cyclin expression and modulate the activity of Cdk inhibitors such as p21 and p27, promoting cell cycle entry and progression. In particular, mechanical strain has been shown to activate the yes-associated protein (YAP), a transcriptional regulator that promotes cell growth and proliferation, leading to β-catenin-mediated gene expression and G1 to S phase transition in bone cells. This mechanically induced proliferation contributes to the adaptive response of bone tissue to altered loading conditions [24,25].

The contractile properties of bone cells also undergo dynamic regulation throughout the cell cycle, influencing their interactions with the surrounding matrix [26]. Measurements of cell traction forces reveal increases during the G1 and S phases, followed by decreases during the G2 phase, corresponding to changes in focal adhesion size and cytoskeletal organization [27]. This temporal coordination between cell cycle progression and mechanical properties ensures appropriate cellular responses to the mechanical microenvironment, particularly during bone remodelling processes [28].

Computational Models of Bone Remodeling

Computational modelling of bone remodelling has emerged as a powerful approach to understand the complex interplay between mechanical loading, cellular responses, and structural adaptation in bone tissue. These models typically incorporate mathematical descriptions of the biological processes involved in bone turnover, coupled with numerical methods to solve the resulting equations across spatial and temporal domains. Among the various numerical approaches, finite element analysis (FEA) has become the predominant method for simulating bone remodelling due to its ability to handle complex geometries and heterogeneous material properties characteristic of bone tissue [30].

Strain-Adaptive Finite Element Models

Strain-adaptive bone remodelling models represent a well-established computational approach that couples mechanical stimuli with changes in bone density and architecture. These models operate on the fundamental principle that bone adaptation

is driven by local mechanical signals detected by bone cells, which subsequently initiate appropriate remodelling responses to optimize the structure according to the prevailing loading conditions [31]. Within this framework, bone density serves as the primary variable characterizing the internal morphology of bone, with its spatial distribution evolving in response to mechanical stimulation [32].

The implementation of strain-adaptive models within finite element frameworks typically involves solving coupled partial differential equations that describe both the mechanical equilibrium of the structure and the temporal evolution of bone density [33]. The spatial domain is discretized using finite elements, while temporal derivatives are typically handled through explicit time-stepping schemes such as the Euler method. This numerical approach allows for the simulation of bone adaptation processes over clinically relevant time scales, providing insights into the long-term consequences of altered loading conditions or surgical interventions [34].

Validation of these computational models involves both qualitative and quantitative comparisons with experimental data. Qualitative validation typically focuses on the spatial distribution of bone density predicted by the model, compared against radiographic images of actual bone structures [35]. Quantitative validation often employs bone mineral density measurements obtained through calibrated imaging techniques, enabling direct comparison of simulated and measured density values at corresponding anatomical locations [36]. These validation procedures ensure that the computational models accurately capture the essential features of bone adaptation processes.

Piezoelectric-Enhanced Bone Remodelling Models

The incorporation of piezoelectric effects into bone remodelling simulations represents a significant advancement in capturing the metaphysical nature of bone adaptation processes. Piezoelectric-enhanced models extend traditional strain-adaptive approaches by introducing electromechanical coupling, wherein mechanical deformation generates electrical potentials that influence cellular behaviour and tissue remodelling [37]. This approach acknowledges the bioelectrical aspects of bone physiology that contribute to its adaptive responses to mechanical loading [38].

Implementation of piezoelectric bone remodelling models requires the solution of coupled electromechanical field equations, typically through finite element methods that handle both mechanical and electrical variables simultaneously [39]. The constitutive relationships between these fields incorporate material properties that describe both the mechanical behaviour of bone and its piezoelectric characteristics, capturing the complex interplay between deformation, electrical potentials, and biological responses. These models have demonstrated that electrically stimulated bone surfaces enhance bone deposition, consistent with experimental observations of electrically induced osteogenesis [40].

Computational simulations incorporating piezoelectric effects have revealed potential therapeutic applications for electrical stimulation in addressing bone loss associated with disuse or pathological conditions such as osteoporosis [41]. By complementing mechanical stimuli from physical activities with targeted electrical stimulation, it may be possible to enhance bone formation in patients with impaired mobility or metabolic bone disorders [42]. These findings highlight the translational potential of piezoelectric bone modelling in developing novel interventions for orthopaedic and rehabilitative applications.

Open-Source Implementations and Reproducibility

Recent developments in computational bone remodelling have emphasized the importance of accessibility and reproducibility through open-source software frameworks [43]. The implementation of bone remodelling algorithms using platforms such as Fenik's provides the scientific community with accessible tools for simulating complex bone adaptation processes without proprietary constraints. These open-source approaches facilitate collaborative development, validation, and application of computational models across various research domains [44].

The workflow for implementing finite element bone remodelling models typically begins with medical image processing to extract anatomical geometries [45]. Specialized software such as AMIRA is often used for segmentation of bone structures from radiographic images, generating point clouds that define the contours of the bone. These geometrical data are subsequently processed through open-source meshing platforms like Salome and Gash to create computational domains suitable for finite element analysis [46]. The resulting mesh files are then converted to appropriate formats for integration with finite element solvers, which perform the numerical simulations of bone remodelling processes.

The adoption of standardized, open-source frameworks enhances the reproducibility of computational studies, allowing independent verification of results and facilitating the comparison of different modelling approaches [47]. This reproducibility is particularly important in the context of patient-specific simulations, where the accuracy and reliability of predictions have direct implications for clinical decision-making. By establishing transparent and accessible methodologies, open-source implementations contribute to the scientific rigor and clinical translation of computational bone remodelling models [48].

Machine Learning Approaches in Bone Tissue Engineering

The integration of Machine Learning (ML) with traditional computational methods has revolutionized the field of bone tissue engineering by addressing computational challenges associated with multiscale modelling and enhancing predictive capabilities. Machine learning approaches offer significant advantages in handling complex, nonlinear relationships between multiple variables that influence bone adaptation and regeneration processes. These data-driven methods complement physics-based

models by providing efficient surrogate models or enhancing parameter estimation for existing mechanistic frameworks.

Machine Learning for Bone Ingrowth Prediction

Recent advancements in machine learning have enabled the development of predictive models for bone ingrowth in scaffolding systems, offering an alternative to computationally intensive multiscale simulations. ML-based approaches correlate scaffold design parameters, material properties, and biological factors with bone regeneration outcomes, establishing predictive relationships without requiring explicit modelling of the underlying physical processes [50]. These models have been validated through dedicated longitudinal animal studies, demonstrating satisfactory accuracy in predicting bone in growth patterns over clinically relevant time periods [51].

Comparison between machine learning predictions and conventional multilevel finite element models has revealed comparable accuracy with substantially reduced computational demands. This computational efficiency enables rapid evaluation of multiple scaffold designs and treatment scenarios, facilitating optimization processes that would be prohibitively expensive using traditional numerical methods alone [51]. The integration of ML approaches with experimental data thus provides an effective means for predicting in vivo bone tissue regeneration in subject-specific scaffolding systems, bridging the gap between computational design and clinical application.

The development of ML-based bone ingrowth models typically involves the collection of comprehensive training datasets that capture the relationship between scaffold properties and bone regeneration outcomes. These datasets include not only the design parameters of the scaffolds but also temporal data on bone formation derived from longitudinal imaging studies, establishing the ground truth for model training and validation. The resulting neural network models can then predict bone in growth patterns for novel scaffold designs not included in the training set, providing valuable insights into the expected performance of these designs prior to experimental testing.

AI-Driven Implant Survival Prediction

Artificial intelligence has demonstrated remarkable capabilities in predicting the survival rates of orthopaedic implants based on patient-specific factors and implant characteristics. Neural network models trained on large clinical datasets have achieved high predictive accuracy in distinguishing between successful osseointegration and implant rejection [52]. These predictive tools incorporate various patient-related factors, including bone quality, medical history, and demographic information, along with implant design parameters to generate personalized risk assessments.

Implementation of such predictive models typically involves artificial neural networks with multiple hidden layers that process complex interactions among input variables. The training process utilizes one-hot encoded statistical factors derived from patient data, with activation functions such as REL (Rectified Linear Unit) for intermediate layers and SoftMax for probabilistic classification of outcomes [53,54]. Models trained on datasets comprising thousands of patient records have achieved test accuracies exceeding 94%, demonstrating the potential of AI approaches in improving clinical decision-making for orthopaedic interventions.

The integration of AI-driven prediction tools into clinical workflows offers significant potential for personalizing implant selection and surgical planning. By identifying patients at higher risk of implant failure, these tools enable proactive interventions such as modified implant designs, enhanced fixation techniques, or adjunctive treatments to promote osseointegration [55]. Furthermore, the continuous refinement of these models through the incorporation of post-operative outcomes creates a feedback loop that progressively improves predictive accuracy and clinical utility [56].

Integration with Finite Element Modeling

The confluence of Machine Learning (ML) and finite element analysis (FEA) has emerged as a computational paradigm for optimizing bone remodelling simulations. Traditional FEA methods, while precise, impose substantial computational overhead, particularly in high-fidelity biomechanical models requiring dense spatial discretization and nonlinear constitutive relationships. To mitigate these constraints, ML algorithms serve as surrogate models, approximating the solution space of computationally expensive FEA simulations while maintaining fidelity in predicting the coupling between mechanical stimuli and osteogenic responses [57].

Multiscale computational frameworks integrating ML and FEA have demonstrated efficacy in modelling hierarchical interactions at the bone-implant interface, where mechanical forces drive localized biological adaptations [58]. At the macroscale, FEA captures stress-strain distributions, global deformation fields, and interface load transfer, whereas ML-based sub models predict microscale mechanotransduction, cellular differentiation, and tissue remodelling kinetics. This hybridized methodology capitalizes on the numerical stability of FEA and the pattern recognition capabilities of ML, enabling real-time parameter sensitivity analysis and inverse problem-solving for personalized implant design [59,60].

Recent advancements in hybrid modelling approaches incorporate Physics-Informed Neural Networks (PINNs), which enforce governing equations-such as equilibrium equations, compatibility conditions, and constitutive laws-within the neural network loss function [61]. By constraining ML predictions to physically admissible solutions, PINNs ensure compliance with mechanobiological principles, circumventing the data inefficiencies and extrapolation errors associated with purely data-driven methods. Additionally, PINNs facilitate adaptive meshing strategies, wherein ML dynamically refines mesh resolution in regions of high stress gradients, optimizing computational efficiency without sacrificing local accuracy [62-64].

Furthermore, generative deep learning architectures, such as variational autoencoders (VAEs) and generative adversarial networks (GANs), have been leveraged to synthesize high-resolution stress-strain maps from sparse FEA datasets [65], enabling rapid exploration of complex material heterogeneities in bone tissue engineering. These advancements bridge the gap between empirical datasets and mechanistic models, accelerating the convergence of computational simulations and experimental validation in bone remodelling studies [66].

Applications in Orthopedic Implant Design and Optimization

Computational modelling approaches combining finite element analysis and machine learning have found extensive application in the design and optimization of orthopaedic implants. These methodologies enable systematic evaluation of implant performance under various loading conditions and patient scenarios, facilitating evidence-based design decisions that enhance clinical outcomes. The integration of patient-specific modeling further allows for personalized implant solutions tailored to individual anatomical and physiological characteristics [67].

Patient-Specific Modeling of Bone-Implant Interfaces

The development of patient-specific models for bone-implant interfaces represents a significant advancement in orthopaedic biomechanics, enabling personalized assessment of implant performance and osseointegration potential [68]. These models utilize medical imaging data to generate accurate representations of patient-specific bone geometries, incorporating individual variations in bone density, architecture, and mechanical properties. The resulting computational domains provide realistic frameworks for simulating the mechanical interactions between implants and surrounding bone tissues [69].

Traditional numerical models of bone-implant complexes often assume perfectly bonded interfaces, which fails to capture the dynamic nature of osseointegration processes [70]. More sophisticated contact analyses incorporating variable friction coefficients have been developed to model different degrees of integration, providing more realistic representations of the evolving bone-implant interface [71]. These models enable the investigation of relationships between implant surface characteristics, bone quality, and interface stability, informing design modifications to enhance osseointegration [72].

Finite element analyses of bone-implant interfaces typically require careful consideration of contact conditions, including normal contact detection and separation behaviour [73]. These analyses reveal critical insights into the mechanical environment experienced by cells at the interface, which directly influences biological responses such as cell proliferation, differentiation, and matrix production [74-76]. By predicting local mechanical stimuli that promote favourable cellular activities, patient-specific modelling guides the development of implant designs that actively enhance biological integration and long-term stability [77].

Mechanoregulatory Principles in Implant Design

The incorporation of mechanoregulatory principles into implant design processes leverages knowledge of how mechanical signals influence bone formation and remodelling [78]. Computational models based on these principles predict tissue differentiation patterns around implants, identifying design features that promote favourable biological responses while minimizing adverse outcomes such as stress shielding or excessive micromotion [79]. This mechanobiological informed approach to implant design represents a paradigm shift from purely mechanical considerations toward designs that actively engage with biological processes [80].

Mechanoregulation-based tissue differentiation algorithms simulate the complex processes of healing and adaptation around orthopaedic implants, predicting the spatial and temporal patterns of tissue formation based on local mechanical stimuli [81]. These simulations incorporate mathematical descriptions of how different mechanical signals influence cellular behaviour and tissue development, allowing designers to optimize implant geometries, material properties, and surface characteristics to promote rapid and robust osseointegration [82].

Adaptive bone remodelling algorithms complement tissue differentiation models by simulating the long-term responses of bone to implanted devices [83]. These simulations predict changes in bone density and architecture that occur over months to years following implantation, identifying potential issues such as stress shielding-induced bone resorption or localized stress concentrations that could lead to mechanical failure [84]. By anticipating these long-term consequences, computational models enable proactive design modifications to ensure sustained implant stability and function throughout the device's intended lifespan [85].

Design Optimization Using Artificial Intelligence

The application of artificial intelligence to implant design optimization has transformed traditional design processes by enabling efficient exploration of vast design spaces and identifying non-intuitive solutions that maximize performance metrics [86]. AI-driven optimization approaches utilize various computational techniques, including genetic algorithms, particle swarm optimization, and reinforcement learning, to iteratively refine implant designs based on performance criteria derived from finite element analyses and tissue differentiation models118. These methodologies automate the design optimization process, generating solutions that would be difficult to identify through conventional design approaches [87].

Machine learning algorithms can efficiently screen large numbers of potential implant designs, rapidly identifying promising candidates for more detailed evaluation through finite element analysis [88]. This tiered approach to design optimization substantially reduces computational requirements while maintaining comprehensive coverage of the design space,

accelerating the development cycle for novel implant technologies [89]. The resulting designs often feature complex geometries and material distributions that optimally distribute mechanical loads and promote favourable biological responses [90].

Recent advancements in generative design approaches powered by artificial intelligence have further expanded the capabilities of implant design optimization [91]. These methods algorithmically generate novel design solutions based on specified constraints and objectives, producing innovative geometries that may not emerge from traditional design processes [92]. When combined with additive manufacturing technologies, generative design enables the realization of complex, optimized implant geometries that were previously infeasible with conventional manufacturing methods, opening new possibilities for patient-specific implant solutions [93].

Future Directions in Computational Bone Modeling

The continued evolution of computational approaches for bone remodelling and implant design presents numerous opportunities for advancing orthopaedic biomechanics and tissue engineering. Emerging technologies and methodologies promise to enhance the accuracy, efficiency, and clinical relevance of these computational tools, accelerating their translation into improved patient care and outcomes [94]. Several key directions for future development warrant particular attention from researchers and clinicians in this field [95].

Advanced Multiphysics and Multiscale Integration

Future developments in computational bone modelling will likely focus on enhanced integration of multiple physical phenomena across relevant spatial and temporal scales [96]. More comprehensive Multiphysics models will incorporate not only mechanical and electrical interactions but also fluid dynamics, solute transport, and chemical reactions that influence bone adaptation processes [97]. These integrated models will provide more realistic representations of the complex physiological environment in which bone remodeling occurs, capturing synergistic effects between different physical stimuli [98].

Multiscale approaches that seamlessly connect molecular, cellular, tissue, and organ-level processes represent another frontier in computational bone modelling [99]. These frameworks will establish mathematical relationships between events occurring at different scales, enabling predictions of how molecular interactions and cellular behaviours manifest as tissue-level adaptations [100]. Advanced numerical methods and computational architectures will be necessary to handle the increased complexity of these multiscale models, potentially leveraging high-performance computing resources and parallel processing techniques [101].

The development of standardized interfaces between computational tools operating at different scales will facilitate more comprehensive simulations of bone adaptation processes [102]. These interfaces will enable efficient information exchange between specialized software packages, creating integrated modelling frameworks that leverage the strengths of various computational approaches [103]. By fostering interoperability between different modelling tools, these standardized interfaces will accelerate the development and validation of multiscale bone remodeling simulations [104].

Real-Time Monitoring and Adaptive Modeling

The integration of computational modelling with real-time monitoring technologies represents a promising direction for enhancing the clinical application of bone remodelling simulations138. Smart implants equipped with sensors that measure local mechanical conditions, biochemical markers, or electrical potentials could provide continuous data for validating and refining computational predictions [105]. These real-time measurements would enable adaptive modelling approaches that continuously update simulation parameters based on actual patient responses, improving prediction accuracy and enabling personalized interventions [106].

Digital twin technologies that create virtual replicas of individual patients' bones and implants could revolutionize treatment planning and monitoring in orthopaedic care [107]. These digital representations would evolve in parallel with the patient's actual tissues, incorporating data from periodic imaging and functional assessments to maintain accuracy over time [108]. By simulating potential interventions on these digital twins, clinicians could evaluate treatment options with minimal risk to patients, optimizing therapeutic strategies based on predicted outcomes [109].

The development of surrogate models using machine learning techniques will enable near-real-time simulation of bone adaptation processes in clinical settings [110]. These computationally efficient models will capture the essential behaviours of more complex simulations, providing rapid feedback to clinicians during surgical planning or postoperative monitoring [111]. As computational resources continue to advance, these surrogate models may eventually approach the accuracy of full-scale simulations while maintaining the speed necessary for interactive applications [112].

Biofabrication and Personalized Implant Design

The convergence of computational modeling with advanced biofabrication technologies offers unprecedented opportunities for creating personalized implants and scaffolds with optimized mechanical and biological properties [113]. Computational models that predict tissue responses to various scaffold designs will guide the development of patient-specific solutions that promote rapid and robust integration with surrounding tissues [114]. These models will incorporate individual variations in bone quality, loading conditions, and regenerative capacity to tailor scaffold properties accordingly [115].

Additive manufacturing technologies will increasingly leverage computational predictions to create complex, hierarchical structures that mimic the natural organization of bone tissue. These biomimetic designs will incorporate features at multiple scales, from microscopic pore networks that facilitate cellular infiltration to macroscopic reinforcements that provide mechanical stability

[116]. The precise control afforded by advanced manufacturing methods will enable the realization of computationally optimized designs that balance competing requirements for mechanical performance and biological integration [117].

The integration of machine learning with bio fabrication processes will enable adaptive manufacturing approaches that continuously refine production parameters based on outcomes [118]. By establishing feedback loops between computational predictions, manufacturing parameters, and experimental results, these systems will progressively improve the correspondence between designed and manufactured implants [119]. This iterative optimization process will enhance the reliability and reproducibility of bio fabricated implants, accelerating their clinical adoption and improving patient outcomes [120].

Conclusion

Computational modelling of bone remodelling has evolved from simplified mechanical analyses to sophisticated metaphysical simulations that capture the complex interplay between mechanical, electrical, and biological processes. The integration of finite element analysis with machine learning approaches has addressed many of the computational challenges associated with simulating these complex phenomena, enabling more comprehensive and efficient explorations of bone adaptation mechanisms. These computational tools have found extensive application in orthopaedic implant design, facilitating evidence-based design decisions that enhance clinical outcomes.

The piezoelectric properties of bone tissue represent a crucial aspect of its mechanobiological behavior, influencing cellular responses to mechanical loading and contributing to adaptation processes. Computational models incorporating these electromechanical interactions have revealed potential therapeutic applications for electrical stimulation in addressing bone loss associated with disuse or pathological conditions. The open-source implementation of these models has enhanced accessibility and reproducibility, facilitating their adoption across various research domains and clinical applications.

Machine learning approaches have demonstrated remarkable capabilities in predicting bone in growth patterns and implant survival rates, offering computationally efficient alternatives to traditional numerical simulations. The synergistic combination of data-driven and physics-based modelling approaches leverages the strengths of both methodologies, providing mechanistic insights while maintaining computational efficiency. As these computational tools continue to evolve, their integration with advanced manufacturing technologies and real-time monitoring systems will further enhance their clinical relevance and impact on patient care.

The continued development of computational approaches for bone remodelling and implant design holds tremendous promise for advancing orthopaedic biomechanics and tissue engineering. By providing deeper insights into the fundamental mechanisms of bone adaptation and enabling the design of implants that actively engage with biological processes, these computational tools will contribute to improved treatments for musculoskeletal disorders and injuries. The interdisciplinary collaboration between engineers, biologists, clinicians, and computer scientists will be essential for realizing the full potential of computational bone modelling in enhancing patient-specific care and outcomes.

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Conflicts of Interest

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