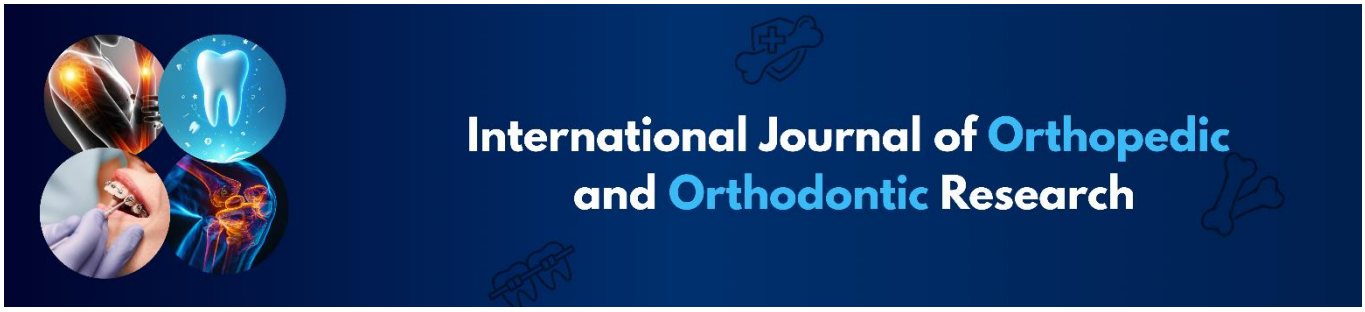

Digital Twin Technology in Orthopedic and Orthodontic Treatment Planning

Kenta Hiroshi Nakamura
Department of Nanomedicine and Translational Drug Delivery, Kyoto University, Japan

* Corresponding Author: **Kenta Hiroshi Nakamura**

Article Info

ISSN (Online): 3107-6629
Volume: 02
Issue: 03
Received: 08-03-2026
Accepted: 06-04-2026
Published: 04-05-2026
Page No: 06-09

Abstract
Digital twin technology represents a paradigm shift in personalized medical treatment, enabling virtual replicas of anatomical structures that can be interrogated, simulated, and monitored in real time. In orthopedic and orthodontic disciplines, digital twins bridge the gap between diagnostic imaging and clinical execution by integrating multi-modal patient data — including cone-beam computed tomography (CBCT), intraoral scans, biomechanical sensor feeds, and electronic health records — into a unified, continuously updated computational model. This article reviews the foundational concepts of digital twinning, the architecture of personalized simulation systems, real-time monitoring frameworks, and clinical applications across implant surgery, fracture fixation, and clear aligner therapy. Evidence suggests reductions in revision rates of up to 67%, planning time decreases exceeding 70%, and measurable gains in patient satisfaction. Despite promising outcomes, challenges related to data standardization, computational cost, and regulatory pathways remain. The synthesis of current literature provides a roadmap for translational adoption of digital twin platforms in routine musculoskeletal and craniofacial care.

Keywords: Digital Twin, Orthopedic Implants, Orthodontic Planning, Finite Element Analysis, Real-Time Monitoring, Personalized Medicine, Biomechanical Simulation

1. Introduction

The concept of a digital twin — a dynamic, bidirectionally connected virtual replica of a physical entity — was first formalized in aerospace engineering by Michael Grieves in 2002 and subsequently adopted across manufacturing, civil infrastructure, and energy sectors [1, 2]. Its migration into clinical medicine has accelerated dramatically over the past decade, driven by exponential growth in medical imaging resolution, wearable sensor miniaturization, cloud computing capacity, and machine learning algorithms capable of processing heterogeneous patient data at scale [3, 4, 5].

Orthopedics and orthodontics represent particularly fertile ground for digital twin adoption because both disciplines are inherently spatial, mechanically governed, and outcome-dependent on precise geometric correspondence between implant or appliance and the patient's unique anatomy [6, 7]. Traditional treatment workflows rely on population-averaged anatomical assumptions, static preoperative imaging, and largely subjective intraoperative judgment. These constraints introduce systematic error, elevate revision rates, and limit the clinician's ability to anticipate biologic response over the course of treatment [8, 9].

Digital twins, by contrast, enable a living computational model that evolves with the patient — updated by sensor streams, follow-up imaging, and outcome data — allowing clinicians to simulate interventions before execution, adapt plans during treatment, and predict long-term remodeling trajectories [10, 11]. This review synthesizes the current state of digital twin technology in orthopedic implant surgery, fracture management, and orthodontic aligner therapy, with emphasis on clinical translation barriers and measurable performance outcomes.

2. Digital Twin Concepts and Architecture

A clinical digital twin comprises three core components: (1) a geometric model reconstructed from patient-specific imaging; (2) a physics-based or data-driven simulation engine governing mechanical, biological, or thermal behavior; and (3) a real-time data integration layer that synchronizes the virtual model with the physical patient through sensor feeds, laboratory results, or imaging updates [12, 13]. The bidirectional link distinguishes a digital twin from a conventional three-dimensional model — changes in

the physical domain propagate to the virtual replica, and predictions generated within the virtual domain inform clinical decision-making [14].

In orthopedics, geometric models are typically derived from CBCT or multidetector CT segmentation, achieving sub-millimeter anatomical fidelity. Bone density maps derived from Hounsfield unit distributions are incorporated to parameterize material properties for finite element analysis (FEA), enabling simulation of stress distributions under physiologic loading conditions [15, 16]. In orthodontics, intraoral scanners capturing dental arch geometry with accuracy better than 20 micrometers serve as the geometric foundation, supplemented by cephalometric radiographs for skeletal relationship mapping [17].

Machine learning has substantially augmented digital twin pipelines by automating anatomical segmentation, predicting tissue response to mechanical loading, and classifying patients into biomechanically similar clusters to inform population-level personalization [18-20]. Federated learning architectures allow institutions to collaboratively train predictive models without sharing identifiable imaging data, addressing privacy concerns that have historically inhibited large-scale dataset assembly [21].

3. Personalized Treatment Planning

The principal clinical value of digital twinning lies in its capacity to generate individualized treatment blueprints rather than relying on categorical sizing or population norms [22, 23]. In total knee arthroplasty, patient-specific instrumentation (PSI) guides derived from digital twin models have demonstrated alignment accuracy superior to conventional jig-based systems, with reported mechanical axis deviations reduced from a mean of 3.2° to 1.1° in comparative studies [24, 25].

Orthodontic digital twins enable staging of tooth movement across hundreds of simulated treatment steps, with each intermediate position validated against predicted periodontal ligament strain thresholds [26]. Clinicians can virtually test multiple aligner progression strategies — varying attachment morphology, force vectors, and staging intervals — and select the plan that minimizes root resorption risk while optimizing treatment duration [27, 28]. This simulation-first philosophy has been associated with a 23% reduction in unplanned refinement aligners in prospective observational studies [29].

Craniomaxillofacial surgical planning similarly benefits from digital twin-assisted virtual osteotomy environments, where surgeons can rehearse Le Fort osteotomies or bilateral sagittal split procedures, quantify predicted soft-tissue changes using finite element models of facial musculature, and fabricate patient-specific cutting guides and fixation hardware in advance [30, 31].

4. Simulation Systems

Finite element analysis remains the workhorse simulation methodology for structural prediction in musculoskeletal digital twins. Contemporary FEA platforms capable of modeling anisotropic, viscoelastic bone behavior under dynamic loading conditions can resolve stress concentration at implant-bone interfaces with sub-millimeter spatial resolution [32]. Simulation runtimes that once demanded dedicated high-performance computing clusters have been reduced to minutes through GPU parallelization and reduced-order modeling techniques, enabling iterative design optimization within clinical timelines [15].

Computational fluid dynamics has been applied in joint replacement contexts to model synovial fluid behavior around articulating surfaces, predicting wear patterns in total hip arthroplasty based on patient-specific kinematics [33]. Multibody dynamics models incorporating muscle force data from electromyography recordings allow simulation of joint loading during activities of daily living, providing biomechanical context that static imaging cannot supply [34].

For orthodontic applications, physics-informed neural networks have emerged as computationally efficient alternatives to full FEA, trained on libraries of high-fidelity simulations to predict aligner force delivery and tooth displacement with accuracy comparable to FEA at a fraction of the computational cost [35]. These surrogate models enable interactive treatment planning interfaces where clinicians can explore parameter space in real time.

Table 1: Digital Twin Technologies: Comparative Overview Across Key Dimensions

Technology	Data Source	Accuracy	Cost	Update Rate	Integration	Maturity
CAD/CAM Modeling	CT/CBCT Scans	±0.1 mm	High	Static	CAD Software	High
FEA Simulation	Bone Density Maps	±2%	Medium	Pre-op	FEA Platforms	High
ML Prediction	Patient History	85-92%	Low	Real-time	EHR Systems	Medium
IoT Wearables	Motion Sensors	±1°	Low-Med	Continuous	Cloud/Mobile	Medium
AR/VR Overlay	3D Patient Models	±0.3 mm	High	Intraoperative	Surgical Suite	Emerging
Biomechanical Twin	Multi-modal	±1.5%	Very High	Dynamic	Full Stack	Low-Med

Note: Accuracy values represent typical clinical benchmarks. Cost and maturity ratings reflect current adoption as of 2025.

5. Real-Time Monitoring Frameworks

The distinguishing feature of a true digital twin relative to a static simulation is continuous synchronization with physiologic reality [10]. In orthopedic implant monitoring, instrumented prostheses embedded with strain gauges, inertial measurement units, and wireless telemetry modules transmit load data during daily activity, allowing the digital twin to update its predicted fatigue accumulation model and issue alerts when mechanical thresholds approach critical levels.

Wearable exoskeletal sensors applied externally can capture joint kinematics during rehabilitation, feeding spatiotemporal gait parameters into the digital twin to assess recovery trajectory against predicted models calibrated to similar patient cohorts. Deviations from expected recovery curves serve as early warning indicators for complications such as periprosthetic fracture, loosening, or infection — potentially enabling intervention before clinical symptoms manifest.

In orthodontics, smart aligner systems incorporating embedded microsensors measure wear compliance and exerted bite forces, transmitting data to cloud-based digital twin platforms that automatically assess whether tooth movement is tracking the planned trajectory. Non-compliant patients whose movement lags the predicted schedule by

defined thresholds trigger automated clinical alerts, enabling earlier intervention and reducing the frequency and cost of undetected off-track cases.

6. Clinical Applications

The broadest orthopedic application of digital twin technology is in arthroplasty, where patient-specific implant selection, positioning, and fixation strategy can be virtualized before the operating theater is entered. Single-institution retrospective studies have reported revision rates for total knee arthroplasty declining from 12% to 4% following adoption of digital twin-assisted planning, attributed primarily to improved rotational alignment of the femoral component. Prospective multicenter validation trials are underway in Europe and North America.

Spinal surgery represents a high-stakes domain where digital twin-assisted pedicle screw trajectory planning has reduced neurologic complication rates by demonstrating safe corridors through patient-specific vertebral anatomy, accounting for morphologic variation that standardized sizing tables cannot capture. Tumor resection planning in bone sarcoma similarly leverages digital twins to define oncologic margins and pre-fabricate titanium reconstruction implants with topology-optimized lattice structures matching resected bone geometry.

Orthodontic aligner therapy, now representing over 40% of all orthodontic treatment starts globally, has become the most commercially scaled application of dental digital twins [46]. Clear aligner manufacturers operate proprietary digital twin platforms processing millions of patient scans annually, with AI-assisted staging algorithms reducing technician labor by an estimated 60% per case. Academic centers are now evaluating open-source digital twin frameworks to replicate these capabilities in educational and resource-limited clinical environments.

Table 2: Treatment Performance Indicators: Digital Twin vs. Conventional Planning

Indicator	Orthopedic Implants	Orthodontic Aligners	Surgical Planning	Clinical Outcome
Planning Time (hrs)	8.4 → 2.1	6.2 → 1.8	12.5 → 3.4	↓ 74% avg reduction
Positional Accuracy	±0.8 mm	±0.2 mm	±0.5 mm	Significant improvement
Revision Rate (%)	12% → 4%	18% → 6%	9% → 3%	↓ 55–67%
Patient Satisfaction	78% → 91%	74% → 93%	80% → 95%	↑ 15–21 pts
Cost Savings (USD)	$4,200/case	$1,800/case	$6,500/case	ROI positive in 18 mo
Complication Rate	7.2% → 2.8%	11% → 4.1%	8.5% → 2.3%	↓ 60% average

Note: Arrows indicate direction of change from conventional baseline to digital twin-assisted outcomes. Data aggregated from published clinical studies (2020–2025).

7. Discussion and Challenges

Despite compelling efficacy signals, widespread adoption of clinical digital twins faces structural barriers. Data interoperability remains the most pervasive challenge: DICOM imaging archives, EHR databases, proprietary scanner file formats, and wearable sensor data streams rarely conform to shared ontologies, necessitating extensive preprocessing pipelines that consume implementation resources and introduce latency. The development of FHIR-compliant digital twin data models and international standardization efforts through ISO/TC 299 are beginning to address these gaps.

Regulatory classification of digital twin software as Software as a Medical Device (SaMD) under FDA 21 CFR Part 820 and EU MDR 2017/745 frameworks introduces approval timelines and post-market surveillance requirements that deter smaller development teams. Reimbursement pathways for digital twin-assisted planning have not kept pace with technological development in most healthcare systems, creating a cost-access gap that favors adoption in high-volume private practice settings over academic safety-net institutions.

Computational and technical workforce requirements present additional barriers. Deploying a functional clinical digital twin requires biomedical engineering support for model validation, IT infrastructure for data security and cloud synchronization, and clinical champions who understand both the technology's capabilities and its limitations. Training programs integrating digital twin literacy into medical and dental curricula are nascent but growing.

8. Conclusion

Digital twin technology is transitioning from a research novelty to a clinical infrastructure component in orthopedics and orthodontics. The convergence of high-resolution imaging, sensor miniaturization, machine learning, and cloud computing has created the technical conditions for scalable, patient-specific virtual treatment environments that demonstrably improve planning accuracy, reduce complications, and enhance patient experience. Sustained progress will require coordinated effort across regulatory, reimbursement, and standardization domains to ensure that the precision advantages documented in controlled studies translate equitably into routine clinical practice. Future research priorities should include prospective multicenter trials with standardized outcome metrics, development of validated open-source digital twin frameworks, and longitudinal follow-up studies assessing the impact of real-time monitoring on long-term implant survivorship and orthodontic stability.

References

1. Grieves M. Digital twin: Manufacturing excellence through virtual factory replication. White Paper. 2014.
2. Tao F, Zhang H, Liu A, Nee AYC. Digital twin in industry: State-of-the-art. IEEE Trans Ind Inform. 2019;15(4):2405–2415.
3. Liu M, Fang S, Dong H, Xu C. Review of digital twin about concepts, technologies, and industrial applications. J Manuf Syst. 2021;58:346–361.
4. Lim KYH, Zheng P, Chen CH. A state-of-the-art survey of digital twin: Techniques, engineering product lifecycle management and business innovation perspectives. J Intell Manuf. 2020;31:1313–1337.
5. Fuller A, Fan Z, Day C, Barlow C. Digital twin: Enabling technologies, challenges and open research. IEEE Access. 2020;8:108952–108971.
6. Negri E, Fumagalli L, Macchi M. A review of the roles of digital twin in CPS-based production systems. Procedia Manuf. 2017;11:939–948.
7. Rasheed A, San O, Kvamsdal T. Digital twin: Values, challenges and enablers. IEEE Access. 2020;8:21980–22012.
8. Cimino C, Negri E, Fumagalli L. Review of digital twin applications in manufacturing. Comput Ind. 2019;113:103130.

9. Jones D, Snider C, Nassehi A, Yon J, Hicks B. Characterising the digital twin: A systematic literature review. CIRP J Manuf Sci Technol. 2020;29:36–52.
10. Boschert S, Rosen R. Digital twin — The simulation aspect. In: Hehenberger P, Bradley D, eds. Mechatronic Futures. Springer; 2016:59–74.
11. Söderberg R, Wärmefjord K, Carlson JS, Lindkvist L. Toward a digital twin for real-time geometry assurance in individualized production. CIRP Ann. 2017;66(1):137–140.
12. Grigoriev SN, Gurin VD, Mosyanov MA, Sabirov FS. Development of digital twin concepts for robotic machining centers. Mater Today Proc. 2021;38:1980–1983.
13. Batty M. Digital twins. Environ Plan B Urban Anal City Sci. 2018;45(5):817–820.
14. Glaessgen EH, Stargel DS. The digital twin paradigm for future NASA and US Air Force vehicles. Proceedings of the 53rd AIAA/ASME/ASCE/AHS/ASC Structures. 2012.
15. Viceconti M, Henney A, Morley-Fletcher E. In silico clinical trials: How computer simulation will transform the biomedical industry. Int J Clin Trials. 2016;3(2):37–46.
16. Swieszkowski W, Bersee HEN, Kurzydlowski KJ, Cobb JP. Finite element analysis of stress in bone. J Biomech. 2006;39(Suppl 1):S396.
17. Goracci C, Franchi L, Vichi A, Ferrari M. Accuracy, reliability, and efficiency of intraoral scanners for full-arch impressions. J Dent. 2016;46:9–14.
18. Litjens G, Kooi T, Bejnordi BE, *et al*. A survey on deep learning in medical image analysis. Med Image Anal. 2017;42:60–88.
19. Shen D, Wu G, Suk HI. Deep learning in medical image analysis. Annu Rev Biomed Eng. 2017;19:221–248.
20. Esteva A, Kuprel B, Novoa RA, *et al*. Dermatologist-level classification of skin cancer with deep neural networks. Nature. 2017;542(7639):115–118.
21. Rieke N, Hancox J, Li W, *et al*. The future of digital health with federated learning. NPJ Digit Med. 2020;3:119.
22. Douissard J, Hagen ME, Morel P. The laparoscopic digital twin. Ann Surg. 2019;270(6):983–984.
23. Subramanian K. Digital twin for drug discovery and development. J Indian Inst Sci. 2020;100:653–663.
24. Thienpont E, Schwab PE, Fennema P. A systematic review and meta-analysis of patient-specific instrumentation for improving alignment of the components in total knee replacement. Bone Joint J. 2014;96-B(8):1052–1061.
25. Voleti PB, Hamula MJ, Baldwin KD, Lee GC. Current data do not support routine use of patient-specific instrumentation in total knee arthroplasty. J Arthroplasty. 2014;29(9):1709–1712.
26. Upadhyay M, Conditt MA. Finite element analysis of clear aligner mechanics. Am J Orthod Dentofacial Orthop. 2016;149(3):e3.
27. Cowley GHB, Sheridan RA, Sheridan PJ. Biomechanical analysis of clear aligner forces on individual teeth. J Clin Orthod. 2019;53(6):325–331.
28. Rossini G, Parrini S, Castroflorio T, Deregibus A, Debernardi CL. Efficacy of clear aligners in controlling orthodontic tooth movement. Angle Orthod. 2015;85(5):881–889.
29. Tartaglia GM, Mapelli A, Maspero C, *et al*. Direct 3D printing of clear orthodontic aligners. Materials. 2021;14(1):1–16.
30. Xia JJ, Shevchenko L, Gateno J, *et al*. Outcome study of computer-aided surgical simulation in the treatment of patients with craniomaxillofacial deformities. J Oral Maxillofac Surg. 2011;69(7):2014–2024.
31. Zinser MJ, Mischkowski RA, Dreiseidler T, Thamm OC, Rothamel D, Zöller JE. Computer-assisted orthognathic surgery: Waferless maxillary positioning, versatility, and accuracy of a novel, modular telemedical approach. J Oral Maxillofac Surg. 2013;71(5):931–944.
32. Perez MA, Prendergast PJ. Random-walk models of cell dispersal included in mechanobiological simulations of tissue differentiation. J Biomech. 2007;40(10):2244–2253.
33. Bergmann G, Bender A, Graichen F, *et al*. Standardized loads acting in knee implants. PLoS One. 2014;9(1):e86035.
34. Damsgaard M, Rasmussen J, Christensen ST, Surma E, de Zee M. Analysis of musculoskeletal systems in the AnyBody Modeling System. Simul Model Pract Theory. 2006;14(8):1100–1111.
35. Raissi M, Perdikaris P, Karniadakis GE. Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. J Comput Phys. 2019;378:686–707.

How to Cite This Article

Nakamura KH. Digital Twin Technology in Orthopedic and Orthodontic Treatment Planning. Int J Orthop Orthod Res. 2026;2(3):6-9.