



Can AI transform biofabrication for clinical translation?

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“By successfully integrating artificial intelligence (AI) into research workflows, researchers could substantially increase scientific productivity” [1]. In biofabrication, AI is driving a paradigm shift from empiricism toward intelligent, data-centric manufacturing [2]. By integrating computation, automation, and biology, AI gives rise to self-evolving, adaptive systems that learn from data, predict complex behaviors, and autonomously optimize fabrication outcomes. Such systems translate experimental insights into patient-specific and clinically relevant solutions, bridging laboratory research and regenerative therapies [3]. This emerging frontier is rapidly advancing from concept to application. This Special Column highlights how AI-driven advances in materials, design, and manufacturing are reshaping biofabrication for regenerative medicine and clinical translation.

1 Data-driven materials discovery

In materials discovery, AI is transforming biomaterials research from trial-and-error exploration to an autonomous, predictive, and self-validating paradigm [4]. Researchers can now achieve closed-loop design and autonomous synthesis of functional biomaterials through integration of data mining, computational modeling, machine learning, and robotic experimentation [5]. Gerbrand Ceder’s group at UC Berkeley exemplified this shift by autonomously producing 41 new inorganic compounds within days [6]. Building on

this, Jianping Gong’s group at Hokkaido University showed that data-driven design can create materials with unprecedented properties, exemplified by a record-breaking underwater adhesive hydrogel [7]. In this Special Column, Zhuo Xiong’s group at Tsinghua University further advanced this paradigm by developing a physics-informed AI framework that decodes the rheological behaviors of bioinks and supporting baths to optimize bioink–bath combinations [8]. Together, these advances illustrate how AI is bridging computation and experimentation, accelerating the discovery and translation of functional biomaterials for real-world applications.

2 Model-guided structural design

AI is shaping multi-scale, functionally guided architectures through intelligent, data-driven design. Alison Marsden’s group at Stanford University developed model-guided algorithms to generate organ-scale vascular networks for highly complex tissue geometries with greatly increased speed [9]. Peng Wen’s group at Tsinghua University harnessed active learning to strengthen porous bone grafts while adaptively tuning their geometry and modulus to match those of native bone tissue [10]. These advances demonstrate how computational intelligence can systematically link structure and function across scales, producing clinically relevant constructs with optimized mechanical and biological features. In this Special Column, Changchun Zhou’s group at Sichuan University introduced a compelling case study in which AI-assisted designs were used to develop a personalized surgical plan and 3D-printed prosthesis for complex bone defects, achieving favorable clinical outcomes [11]. This approach offers a paradigm for precision treatment in challenging orthopedic cases and highlights the translational promise of AI-guided personalized medicine.

3 Closed-loop adaptive biofabrication

In process control, AI is transforming biofabrication by integrating real-time monitoring, predictive adjustments, and

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autonomous process control [12]. Robert K. Katzschmann's group at ETH Zurich achieved AI-assisted computer vision in multi-material jetting, enabling real-time feedback and geometric correction without manual calibration [13]. Similarly, Riccardo Levato's group at Utrecht University combined imaging, computing, and parametric modeling for perception-driven volumetric printing, allowing printers to "see, learn, and decide" during fabrication [14]. Such approaches shift biofabrication from preprogrammed execution to adaptive, self-correcting processes with unprecedented precision, reproducibility, and operational autonomy. In this Special Column, Jiacan Su's group at Shanghai University summarized AI-enabled strategies for in situ monitoring and process optimization, including in situ bioprinting for tissue repair [15]. Geng Yang's group at Zhejiang University reviewed how AI-driven closed-loop frameworks are reshaping robotic electronic skins, enabling multimodal sensing, enhanced perception, and intelligent human-machine interaction relevant to soft robotics and bio-integrated systems [16]. These advances identify intelligent feedback control as a pivotal factor for constructing complex tissue architectures and expediting translation of engineered tissues toward clinical application.

4 Predictive clinical translation

For clinical translation, AI is facilitating predictive, standardized, and reproducible biofabrication to meet clinical and regulatory requirements. Rongrong Zhu's group at Tongji University used deep learning to predict neural stem cell differentiation within 24 h of induction [17], improving quality control for regenerative therapies. Peter Horvath's group at the HUN-REN Biological Research Centre developed an AI-driven, high-content 3D organoid screening platform that accelerates drug discovery and toxicity testing with single-cell resolution [18]. In this Special Column, Zhongze Gu's group at Southeast University developed a deep learning algorithm for segmenting challenging organoids under simple bright-field imaging conditions to promote rapid exclusion of various artifacts and streamline organoid analysis and drug screening workflows [19]. These advances emphasize the importance of intelligent monitoring and predictive analytics for bridging bench-scale fabrication and clinical deployment, paving the way for safer, more efficient, and personalized regenerative interventions [20].

5 Challenges and opportunities

Despite this remarkable progress in AI-powered biofabrication, key challenges remain. Limited availability of standardized datasets, high biological variability, and incomplete

understanding of multi-scale mechanobiology complicate predictive modeling [21]. Integrating heterogeneous data from molecular, cellular, and structural levels into interpretable, actionable frameworks requires new algorithms, robust infrastructures, and cross-disciplinary collaboration. Regulatory systems must also evolve to assess adaptive, self-optimizing platforms. Addressing these challenges will be essential to realizing AI-powered biofabrication that not only learns, adapts, and personalizes regenerative outcomes, but also realizes its transformative potential for clinical translation, a vision that this Special Column brings into focus.

References

- Gil D, Moler KA (2025) Accelerating science with AI. *Science* 390(6777):965. <https://doi.org/10.1126/science.aee0605>
- Wu C, Entezari A, Zheng K et al (2021) A machine learning-based multiscale model to predict bone formation in scaffolds. *Nat Comput Sci* 1:532–541. <https://doi.org/10.1038/s43588-021-00115-x>
- Yuan XM, Kong WC, Shao YJ et al (2025) AI-feedback bioelectronics promote infectious wound healing. *Cell Biomater* (early access). <https://doi.org/10.1016/j.celbio.2025.100191>
- Burger B, Maffettone PM, Gusev VV et al (2020) A mobile robotic chemist. *Nature* 583:237–241. <https://doi.org/10.1038/s41586-020-2442-2>
- Steiner S, Wolf J, Glatzel S et al (2019) Organic synthesis in a modular robotic system driven by a chemical programming language. *Science* 363(6423):eaav2211. <https://doi.org/10.1126/science.aav2211>
- Szymanski NJ, Rendy B, Fei Y et al (2023) An autonomous laboratory for the accelerated synthesis of novel materials. *Nature* 624:86–91. <https://doi.org/10.1038/s41586-023-06734-w>
- Liao HG, Hu S, Yang H et al (2025) Data-driven de novo design of super-adhesive hydrogels. *Nature* 644:89–95. <https://doi.org/10.1038/s41586-025-09269-4>
- Zhou XH, Zhang ZR, Yu JT et al (2026) AI-driven interpretation and prediction of embedded printability based on rheology. *Bio-Des Manuf* 9(1):63–79. <https://doi.org/10.1631/bdm.2500456>
- Sexton ZA, Rutsche D, Herrmann JE et al (2025) Rapid model-guided design of organ-scale synthetic vasculature for biomanufacturing. *Science* 388(6752):1198–1204. <https://doi.org/10.1126/science.adj6152>
- Peng B, Wei Y, Qin Y et al (2023) Machine learning-enabled constrained multi-objective design of architected materials. *Nat Commun* 14:6630. <https://doi.org/10.1038/s41467-023-42415-y>
- Han YL, Lei HY, Jia RZ et al (2026) AI-assisted design of 3D-printed prosthesis for integrated replacement of the hip, femur, and knee caused by osseous hydatidosis. *Bio-Des Manuf* 9(1):94–99. <https://doi.org/10.1631/bdm.2500162>
- Mo XW, Zhang YM, Wang ZX et al (2024) Satellite-based on-orbit printing of 3D tumor models. *Adv Mater* 36(34):2309618. <https://doi.org/10.1002/adma.202309618>
- Buchner TJK, Rogler S, Weirich S et al (2023) Vision-controlled jetting for composite systems and robots. *Nature* 623:

- 522–530.
<https://doi.org/10.1038/s41586-023-06684-3>
14. Florczak S, Größbacher G, Ribezzi D et al (2025) Adaptive and context-aware volumetric printing. *Nature* 645:108–114.
<https://doi.org/10.1038/s41586-025-09436-7>
 15. Bai L, Zhang Y, Wang SC et al (2026) Artificial intelligence-enabled Bioprinting 5.0. *Bio-Des Manuf* 9(1):32–62.
<https://doi.org/10.1631/bdm.2400354>
 16. Wang BC, Kong DP, Yang HY et al (2026) AI-powered electronic skin: from smart design to cognitive interaction. *Bio-Des Manuf* 9(1):4–31.
<https://doi.org/10.1631/bdm.2500376>
 17. Zhu YJ, Huang RQ, Wu ZR et al (2021) Deep learning-based predictive identification of neural stem cell differentiation. *Nat Commun* 12:2614.
<https://doi.org/10.1038/s41467-021-22758-0>
 18. Diosdi A, Toth T, Harmati M et al (2025) HCS-3DX, a next-generation AI-driven automated 3D-oid high-content screening system. *Nat Commun* 16:8897.
<https://doi.org/10.1038/s41467-025-63955-5>
 19. Du X, Li YC, Song JP et al (2026) Precision organoid segmentation technique (POST): accurate organoid segmentation in challenging bright-field images. *Bio-Des Manuf* 9(1):80–93.
<https://doi.org/10.1631/bdm.2500119>
 20. Tebon PJ, Wang B, Markowitz AL et al (2023) Drug screening at single-organoid resolution via bioprinting and interferometry. *Nat Commun* 14:3168.
<https://doi.org/10.1038/s41467-023-38832-8>
 21. Rivenson Y, Wang H, Wei Z et al (2019) Virtual histological staining of unlabelled tissue-autofluorescence images via deep

learning. *Nat Biomed Eng* 3:466–477.
<https://doi.org/10.1038/s41551-019-0362-y>



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