From equations to intelligence: the future of AI-driven computational mechanics

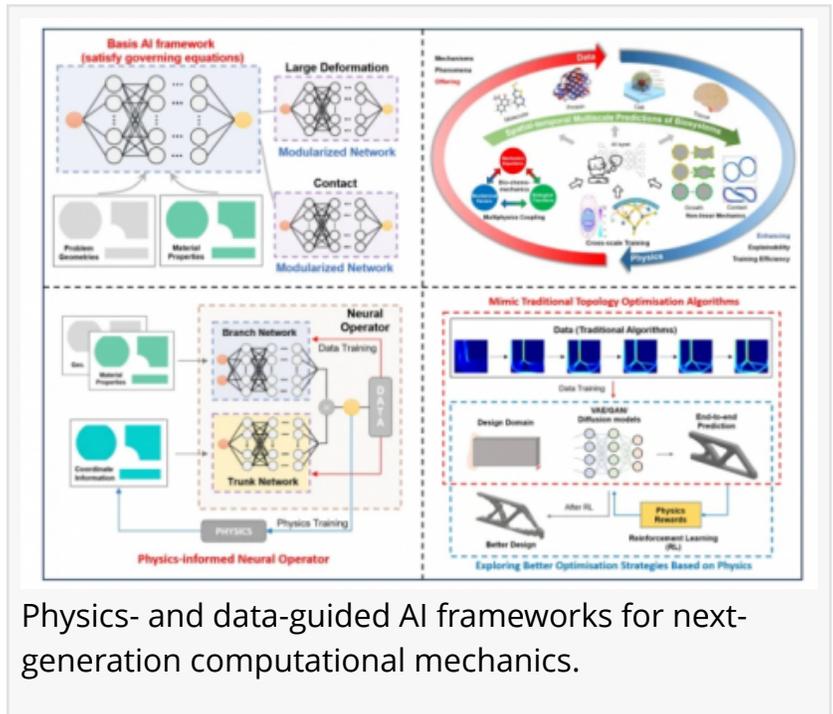FAYETTEVILLE, GA, UNITED STATES, December 31, 2025 / EINPresswire.com/ -- Artificial intelligence (AI) is increasingly transforming computational mechanics, yet many AI-driven models remain limited by poor interpretability, weak generalization, and insufficient physical consistency.

Computational mechanics plays a foundational role in engineering and scientific research, traditionally relying on numerical methods such as the finite element method to solve governing equations. While these approaches are highly effective for

Physics- and data-guided AI frameworks for next-generation computational mechanics.

linear and well-defined problems, they face increasing challenges when addressing nonlinear behavior, multiphysics coupling, and multiscale phenomena. Recent progress in artificial intelligence (AI) has introduced powerful alternatives that accelerate computation and reduce modeling complexity. However, many AI-based approaches depend heavily on large datasets and often lack physical interpretability, limiting their reliability and extrapolation capability. Based on these challenges, there is a growing need to develop deeply integrated physics- and data-guided AI frameworks for computational mechanics.

Researchers from Queensland University of Technology, Tsinghua University, and international partner institutions reported their findings (DOI: 10.1007/s10409-025-25340-x) on July 9, 2025, in Acta Mechanica Sinica. The perspective article reviews the current landscape of AI-enhanced computational mechanics and proposes a unified roadmap for integrating physical laws with data-driven learning. By examining recent developments in physics-informed neural networks (PINNs), neural operators, and intelligent optimization, the study identifies critical bottlenecks and outlines future directions for building robust, generalizable, and efficient AI-powered computational frameworks for engineering and biomechanics applications.

The study analyzes three major paradigms in AI-enabled computational mechanics: purely data-driven models, PINNs, and neural operator learning. Data-driven approaches offer exceptional computational speed but suffer from limited interpretability and poor generalization outside training data. PINNs improve physical consistency by embedding governing equations into the learning process, yet they often encounter convergence difficulties and problem-specific constraints, particularly in multiphysics and time-dependent scenarios. Neural operators extend generalization across problem families but remain data-intensive and may violate physical principles when extrapolating.

To address these challenges, the authors propose four forward-looking research directions. First, modular neural architectures inspired by traditional computational mechanics can embed physical structure directly into network design, enhancing stability and convergence. Second, physics-informed neural operators enable resolution-invariant learning by training directly on governing equations rather than data alone. Third, physics–data-integrated AI frameworks offer unique advantages for multiphysics and multiscale biomechanics, where traditional numerical methods struggle to unify biological processes across scales. Finally, combining physical constraints with reinforcement learning opens new opportunities for structural optimization, allowing AI systems to explore non-intuitive yet physically valid designs. Together, these strategies mark a shift from black-box AI toward foundational, physics-aware intelligent computation.

"AI should not replace physical understanding, but rather amplify it," the authors emphasize. They argue that physics-guided AI frameworks offer a path toward computational models that are not only faster but also more reliable and interpretable. By embedding conservation laws, variational principles, and physical constraints into learning architectures, these approaches reduce uncertainty and improve trustworthiness. According to the researchers, such integration is essential for deploying AI in real-world engineering and biomedical applications, where predictive reliability and physical consistency are critical.

The proposed physics- and data-guided AI frameworks have broad implications across engineering, biomechanics, and materials science. They enable faster and more reliable simulations of complex systems, including soft biological tissues, multiphase flows, and nonlinear structures. In design and optimization, physics-constrained AI combined with reinforcement learning could support real-time exploration of innovative structural configurations that outperform conventional solutions. Beyond efficiency gains, these methods also lay the foundation for digital twin technologies, offering powerful tools for prediction, diagnosis, and optimization. Overall, the study points toward a new generation of intelligent computational tools that balance data-driven flexibility with the rigor of physical laws.

References
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