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ADVANCED PHYSICS-BASED AND DATA-DRIVEN MODELING FOR BIOMEDICAL DIGITAL TWIN

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ABSTRACT

Computational modeling plays a crucial role in biomedical science and engineering. These mathematical models and robust numerical methods contribute significantly to understanding physiological and pathological processes, optimizing medical device design, and enhancing decision-making in clinical trials [1,2]. Furthermore, to enable clinical translation, digital twinning, and in-silico trials, the development of highly efficient and cost-effective techniques for model personalization is essential.

Recent advancements in scientific machine learning offer promising avenues for this purpose [3]. Data-driven approaches, such as deep learning, kernel methods, and reduced-order modeling, provide reliable surrogates for complex biological phenomena by leveraging large datasets while reducing computational costs compared to traditional physics-based models. Additionally, novel hybrid methodologies that integrate physics-based and data-driven techniques, such as physics-informed machine learning, can further mitigate nonphysical artifacts and enhance the generalization of predictive performance [4]. These approaches have also proven effective in solving inverse problems across various biomedical domains. Moreover, probabilistic techniques such as Bayesian optimization and generative approaches are widely applied in model calibration, uncertainty quantification, and virtual population generation, enhancing the reliability and generality of computational estimates [5].

This mini-symposium will bring together applied mathematicians, computational scientists, biomedical engineers, and clinicians to discuss state-of-the-art developments in physics-based

and data-driven methods for computational biomedicine. Topics of interest include, but are not limited to, patient-specific model parameterization and optimization, advanced machine learning methods for real-time modeling and many-query scenarios, robust Bayesian methods for model calibration and uncertainty quantification, the integration of multi-scale models with clinical data for personalized medicine, in-silico trials for regulatory science and therapy evaluation, and the industrial applications of medical digital twins in device design and testing. By fostering discussions on these cutting-edge topics, we aim to encourage future collaborations and expand the international research network in the emerging field of digital health and medical digital twins.

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