Today, billions of light-based medical sensors are used by hospitals to measure quantities like blood flow, temperature, oxygenation and more. Clinical decision-making is partially based on the measurements from these sensors - so it’s important that these sensors measure data robustly. Unfortunately, the accuracy of light-based devices varies across demographics. Just as a soap dispenser may not always work for those with dark skin, a light-based medical device has fundamental challenges at the light-matter interface, leading to degradations in signal-to-noise (SNR) ratio and measurement accuracy. To solve this problem, and make devices more inclusive and even more accurate (for everyone), we need to rethink the sensing process, e.g., what wavelengths are used, what computer algorithms are used, and how datasets are generated. The parameters involved in designing a medical device are complex and high-dimensional, and ultimately only one design can be built. Differentiable computer algorithms are developed that backpropagate gradients to sensing parameters, enabling “learning” of sensing configurations. Learning how to design sensors can be applied to a wide variety of equitable imaging systems that measure heart rate and blood volume (contact-free and wirelessly). Of course learning requires data, and real data is at a scarcity. We also discuss human digital twin data pipelines that model melanin content and the theoretical benefits of minority inclusion on dataset composition. The fusion of novel sensors, physically-based simulators, and AI pipelines lead to novel medical systems deployed at UCLA Hospital to reduce bias (against minority groups), while improving accuracy (for everyone). We close by discussing how the devices studied in this talk are only scratching the surface of biosensors that can be redesigned with increasing fairness and accuracy in mind.