Abstract: Advances in machine learning (ML) have led to modest success in clinical healthcare, as opposed to fields like computer vision. Many research challenges remain that are critical for safe deployment of ML methods for clinical decision support. One of these challenges is related to the ability of ML models to learn clinically relevant and actionable insights. In the first part of my talk I focus on contextualizing these concerns in terms of explainability of ML methods and the widening discrepancy between current ML explainability research and clinician expectations. One such severely understudied problem is determining the individualized feature relevance in time series models. We propose a method to quantify feature importance in this setting by leveraging deep generative models and demonstrate its efficacy on simulated and real world data. While disparities in healthcare have been well documented, the effect of using biased data in ML, especially for causal effect estimation, needs more scrutiny. To that effect, in the second part of my talk, I will describe a method we propose to evaluate the reliability of state of the art ML based counterfactual regression models in the presence of treatment and outcome disparity and relating their efficacy to underlying data generative settings and awareness of the source of disparity. We end with a vision of a research goals toward addressing safe and fair deployment of ML for health.