Abstract
Predicting human decision-making under risk and uncertainty is a longstanding challenge in economics and related fields. While classical theories excel at offering explanations, they often falter in predictive accuracy. The challenge often lies in the idiosyncratic nature of initial choice, whereas repeated decisions with feedback tend to exhibit more stable patterns, allowing for more reliable forecasts. In this talk, I present a novel integrative framework that unites theory-rich behavioral models with machine learning and AI techniques. This approach, as exemplified by the BEAST Gradient Boosting (BEAST-GB) model, not only achieves state-of-the-art predictive accuracy in forecasting human choice behavior—surpassing purely data-driven methods and other behavioral models—but also maintains robust generalization across contexts. Moreover, I will show how insights from human learning processes can enhance machine learning models, helping to anticipate repeated choices more accurately and to identify the conditions under which theoretical structure is most beneficial. Taken together, these findings highlight that combining rich behavioral theories with advanced computational tools can advance both our understanding of human decision-making and our ability to predict it, ultimately benefiting research, policy, and practical applications.