Abstracts

Using Mixed Methods Evidence to Inform Scientific Judgment in Study Design

Noor Qaragholi, The Policy & Research Group

Establishing credible causal relationships is a central goal in science and medicine. Because estimating causal effects often depends on strong, untestable assumptions, researchers must exercise scientific judgment and draw on substantive knowledge to determine whether those assumptions are plausible in a given context. These judgements are integral for drawing credible causal conclusions. Yet, systematic approaches for generating and integrating the needed substantive knowledge into causal analyses remain limited.

One promising but underutilized strategy is the use of mixed methods – the purposeful integration of qualitative and quantitative approaches – to generate and incorporate the substantive knowledge relevant to causal assumptions. Such knowledge can strengthen study design by creating conditions under which assumptions are more likely to hold and can inform assessments of their plausibility. Using key assumptions underlying complier average causal effect (CACE) estimation as an illustrative example, Noor Qaragholi's presentation draws on a randomized trial of a behavioral intervention with substantial noncompliance. More broadly, this work discusses the potential for mixed methods approaches to strengthen study design, make scientific judgement more transparent, and strengthen confidence in causal conclusions.

Causal Neuro-Symbolic AI

Utkarshani Jaimini, University of Michigan - Dearborn

As AI systems become embedded in high-stakes decision-making, accuracy alone is no longer sufficient. We need systems that are explainable, interpretable, and causally aware. The current data-driven models are fundamentally correlational, identifying patterns without understanding the mechanisms behind them. This talk introduces Causal Neuro-Symbolic AI as a framework for bridging this gap combining causal reasoning with neuro-symbolic methods to help AI systems reason about why things happen, not just what tends to co-occur. The talk covers three threads: enriching neuro-symbolic AI with causal representations, integrating causal knowledge with domain expertise, and applying neuro-symbolic techniques to causal discovery. This work spans knowledge representation, causal inference, and applied machine learning.

How Bayesian Trial Design Can Make Scientific Judgment Explicit

Lu (Maggie) Qian, Evidence in the Wild | Zetyra

Bayesian clinical trial design inevitably requires scientific judgment, particularly in specifying prior distributions and determining how external evidence should influence inference. This talk examines how Bayesian methods can make those judgments explicit rather than opaque. Drawing on FDA Bayesian guidance, recent work on reverse-Bayes methods, and practical examples from clinical trial design, I discuss approaches for evaluating prior specification, detecting prior-data conflict, and assessing dynamic borrowing in a transparent, reproducible manner. Rather than viewing priors as subjective inputs to be accepted on faith, these methods provide an auditable framework that strengthens scientific credibility while preserving the flexibility that makes Bayesian designs attractive.

Expert Elicitation for Bayesian Clinical Trial Design

Anna Heath, The Hospital for Sick Children, University of Toronto, University College London

Bayesian methods are increasingly popular in clinical research. However, the design of Bayesian clinical trials requires a prior distribution. One method to obtain these values is through expert elicitation, where experts are supported to turn their experience and expertise into probabilistic statements. Anna Heath and her team have used remote, real-time elicitation exercises to construct prior distributions to support the design of multiple clinical trials. This talk will introduce the challenges and advantages of using expert elicitation for clinical trial design.