A short intro to causal inference with an example from analysis of linked registries

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A classification of data analytic tasks

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2. **Prediction** (e.g. for prognosis or diagnosis)
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See e.g. Shmueli 2010 and Hernan et al. 2019

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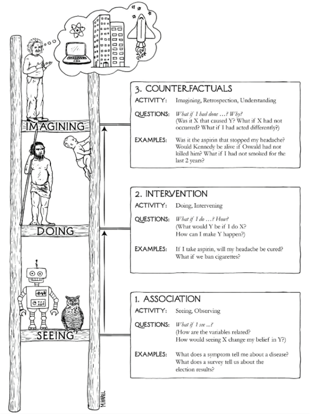
- See also Pearl's **ladder of causation**:



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  Some follow **Holland's mantra** more dogmatically than others, but most would agree it simplifies things...

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- 2020: **ICH E9 (R1) addendum** on estimands and sensitivity analysis in clinical trials

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Can argue that this is a more general principe borrowing the logic of the scientific method

Example using clinical and nation-wide registers

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- How do we study the **effects of early opioid use** on long term use?

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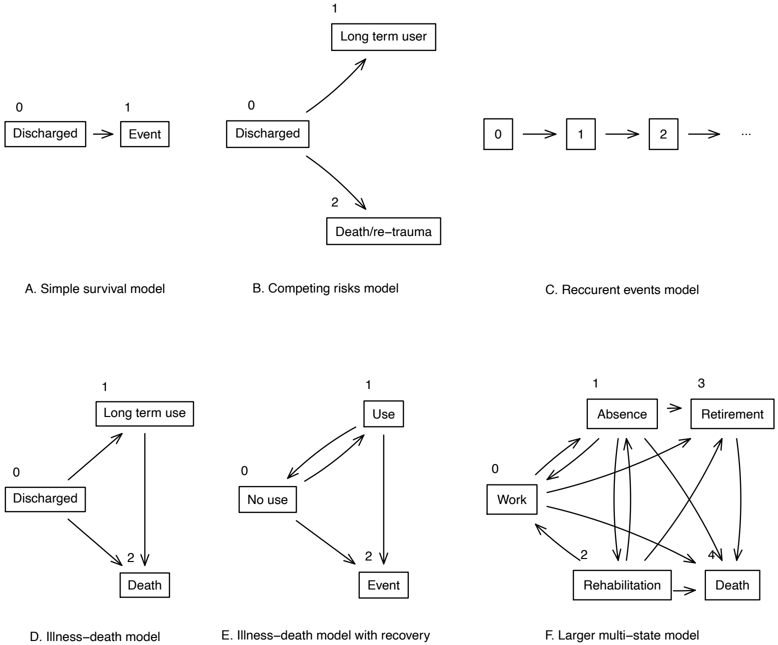
  Write out full protocol as in real RCT: specify eligibility criteria (opioid prescription day 0-14), time zero (14 days after discharge), treatment strategies (as above), baseline adjustment variables (age, sex, income, history of opioid use, geography, injury scores and type, comorbidities, hospital stay characteristics etc), time-varying adjustment variables (health visits in KUHR and NPR, opioids and other drug use) and long term opioid use as outcome (certain amount prescribed over 90 days, followed up by new prescriptions)

- **Broader outcomes of interest**:



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- Interventionism is about studying effects that are testable in principle; in other words it is about being **scientific**
- Causal inference is not about being overly optimistic about causal claims, but **about being transparent and honest**