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IDM Symposium 2024

An End-to-End Approach to Enhance Family Planning Uptake in Madhya Pradesh, India Through Causal AI-Guided Intervention Design to A Cluster RCT

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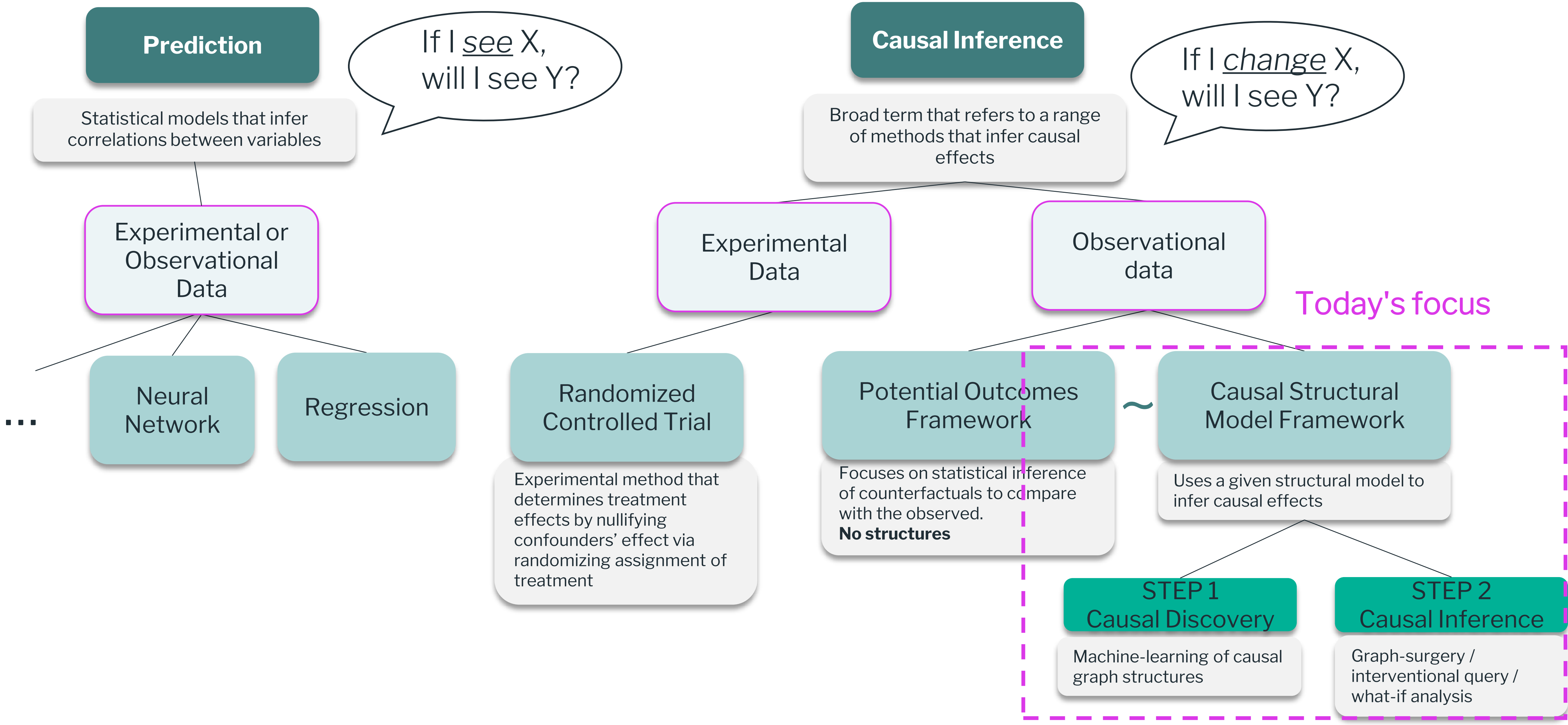
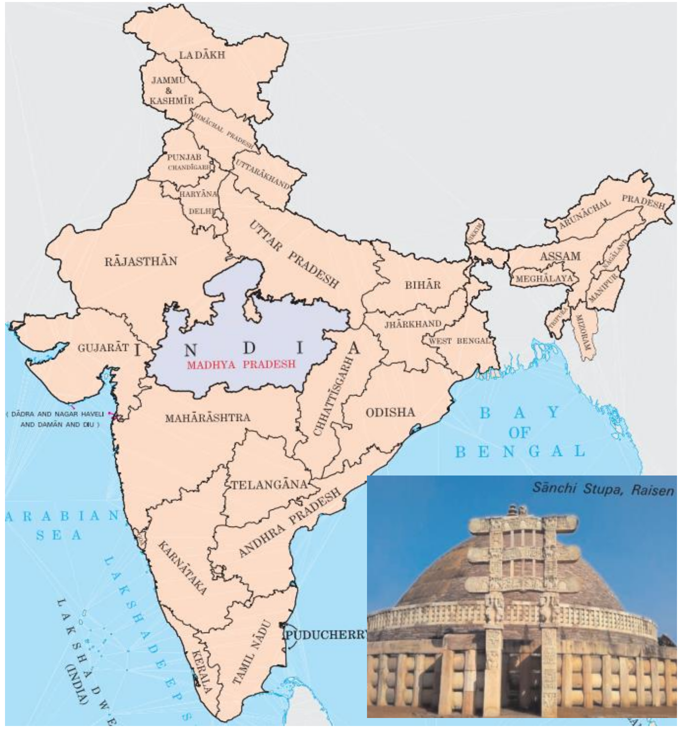
Lay of the land – Prediction vs. Causal Inference



Madhya Pradesh, India




Multi-household dwelling


Typical rural dwelling


"ASHAs"
Community health workers training


"ASHA" (Community health worker) w/ community


Sub-District hospital


Sub-District hospital


Primary health center


Primary health center


Health sub-center

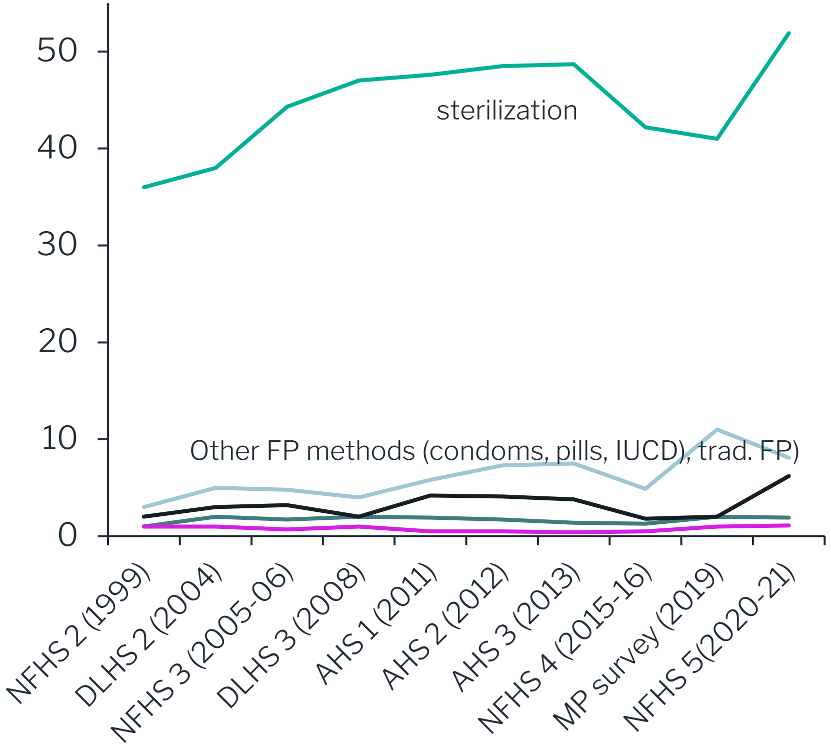

Health sub-center

Uptake of modern effective temporary (MET) family planning methods has remained low despite investments

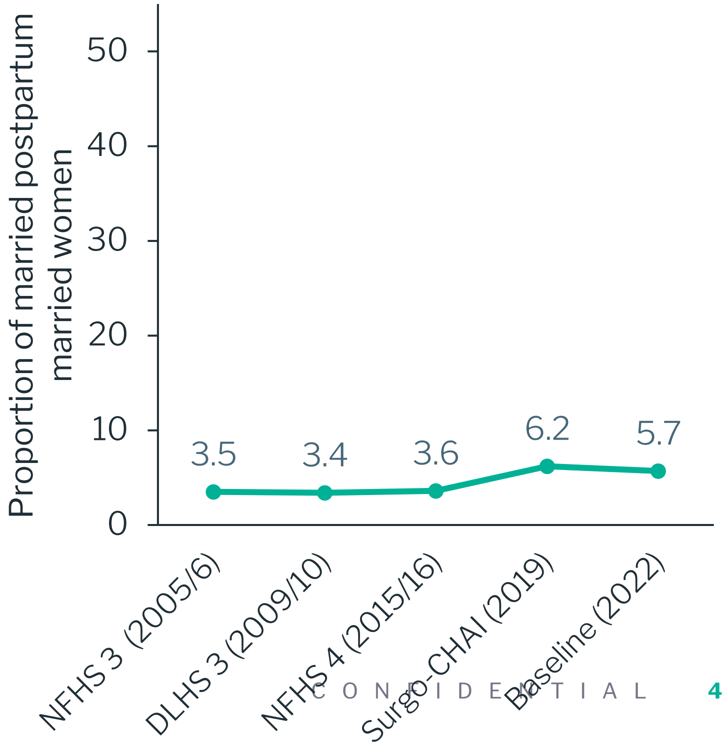
What was happening on the ground?

- **High investments by GoMP & partners** in FP access to new contraceptives
- **Negligible uptick in uptake**:
  - Overreliance on sterilization
- Programs too broad, **lacked focus**
  - CHWs deprioritized FP - low self-efficacy, unclear roles

FP Method mix in MP (%)



Current MET Use (%) (pills, injectables, IUCD)



Predictive modeling falls short: Correlation doesn’t imply causation

Where did predictive models fall short?

- **Misattributed critical causal variables + unclear why:** confounding & lack of direct comparisons

  Predictive model would suggest these correlates as targets that turn out to be not actionable or deeply confounded :*
  - Self-Help Group (SHG) member (confounded by age, etc)
  - Age
  - Believing parity is will of god (confounded by edu level, etc)

- **Increased risk of resource misallocation** and poor impact

Potential for Causal AI

- Need only **observational data** to infer model
- **What to intervene?** Pinpointed high-impact intervention levers
- **How to intervene?** Uncovered cause of causes to define interventions
- **ROI to expect? :** Virtual RCT to estimate impact of causal drivers
- Validation through streamlined real-life RCTs

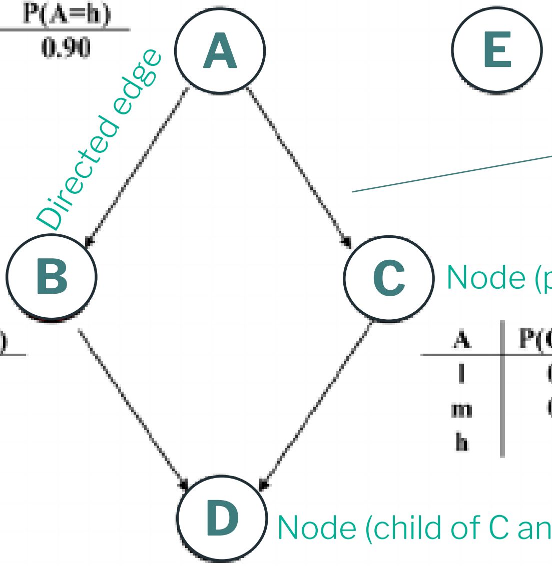
*From the same list of input variables that we later used for causal AI input

STEP 1: LEARNING A CAUSAL STRUCTURAL MODEL

Components of a Causal Bayesian Network model

P(A=l)	P(A=m)	P(A=h)
0.04	0.06	0.90

P(E=l)	P(E=m)	P(E=h)
0.8	0.15	0.05



A	P(B=l|A)	P(B=m|A)	P(B=h|A)
l	0.1	0.1	0.8
m	0.2	0.65	0.15
h	0.7	0.25	0.05

A	P(C=l|A)	P(C=m|A)	P(C=h|A)
l	0.75	0.15	0.1
m	0.15	0.65	0.2
h	0.1	0.2	0.7

B C	P(D=l|B,C)	P(D=m|B,C)	P(D=h|B,C)
l l	0.1	0.2	0.7
m m	0.3	0.6	0.1
h h	0.8	0.1	0.1
l m	0.1	0.3	0.6
m h	0.6	0.3	0.1
h l	0.1	0.7	0.2
l h	0.1	0.8	0.1
m l	0.05	0.15	0.8
h m	0.6	0.3	0.1

Causal Structure
(a directed acyclic graph (DAG))

DAGs Can be learned by **structural learning algorithms** from observational data:
Ex.

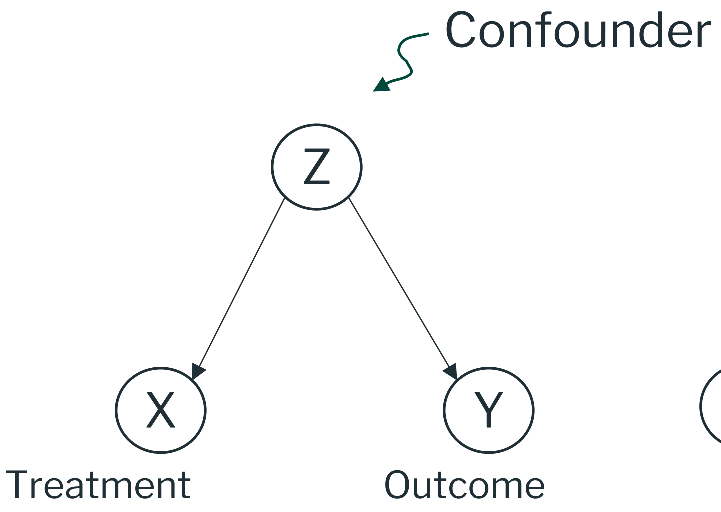
- PC-algorithm (constraint-based) or
- Greedy Equivalence Search (score-based)
- Hybrid algorithms

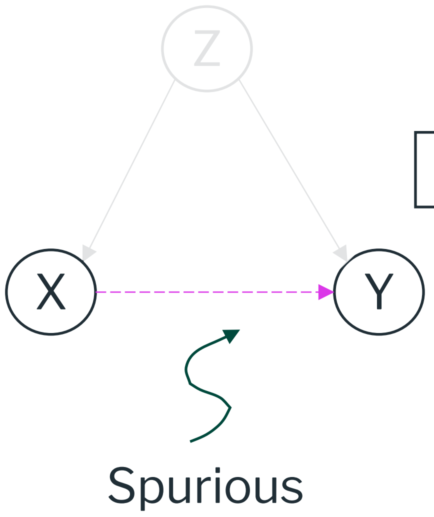
Conditional Probability Table
(for each node)

Can be estimated by **Maximum likelihood estimator**, Bayesian posterior estimator, etc

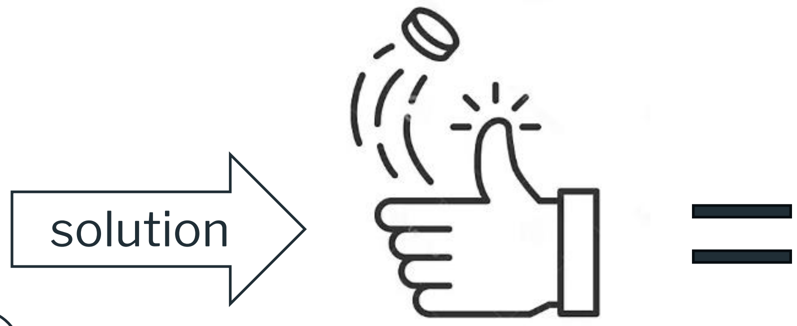
Field et al. (2015). Bayesian modeling suggests that IL-12 (p40), IL-13 and MCP-1 drive murine cytokine networks in vivo. BMC Systems Biology

RCTs are magical because they imply treatment is independent of confounders; We can simulate RCTs by “graph surgery”



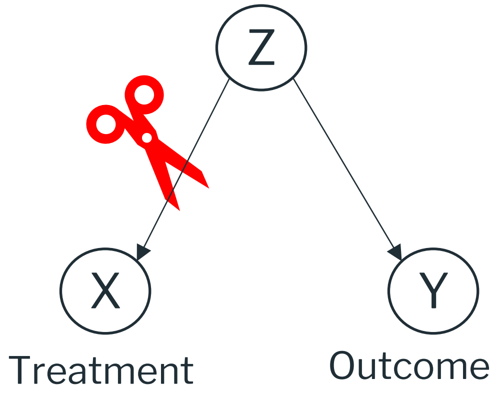


Randomized Controlled Trial



Randomization is the same as dissociating the treatment variable from its causes

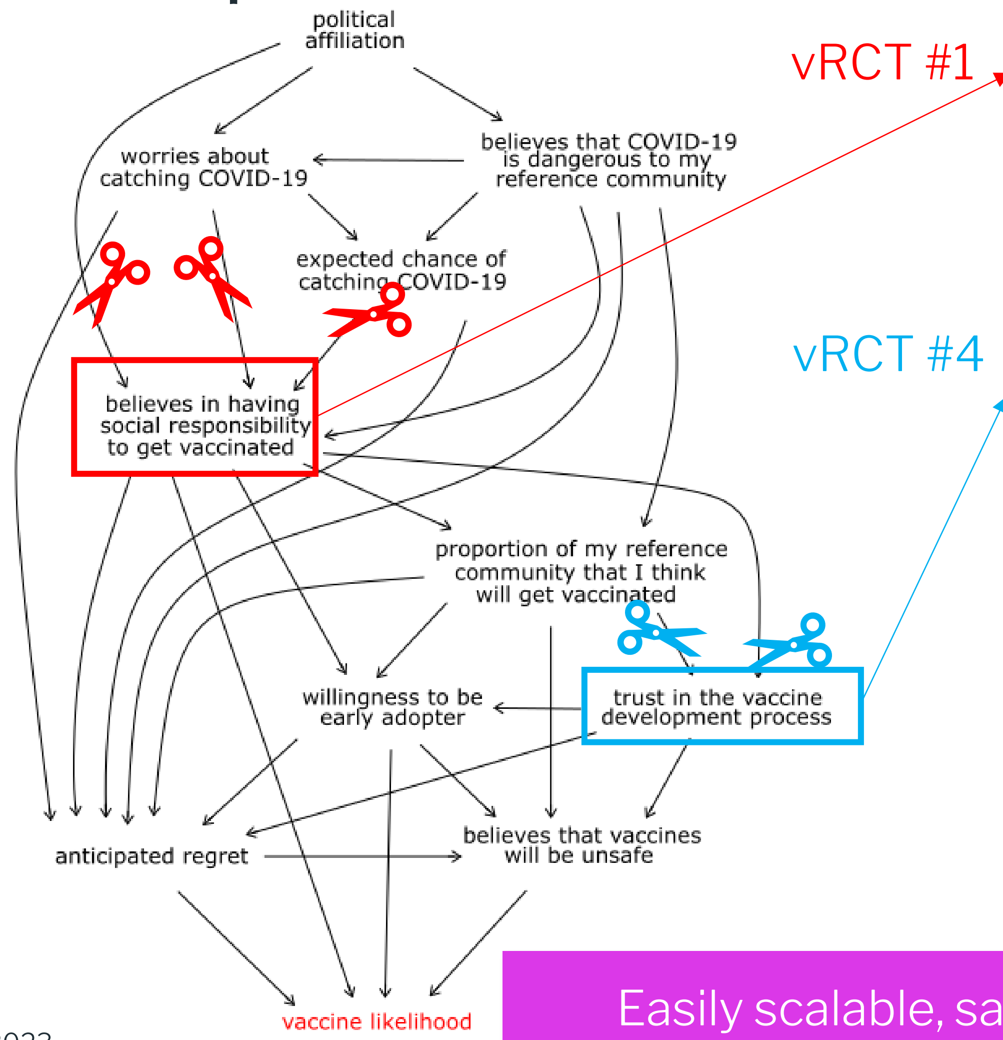
Graph surgery

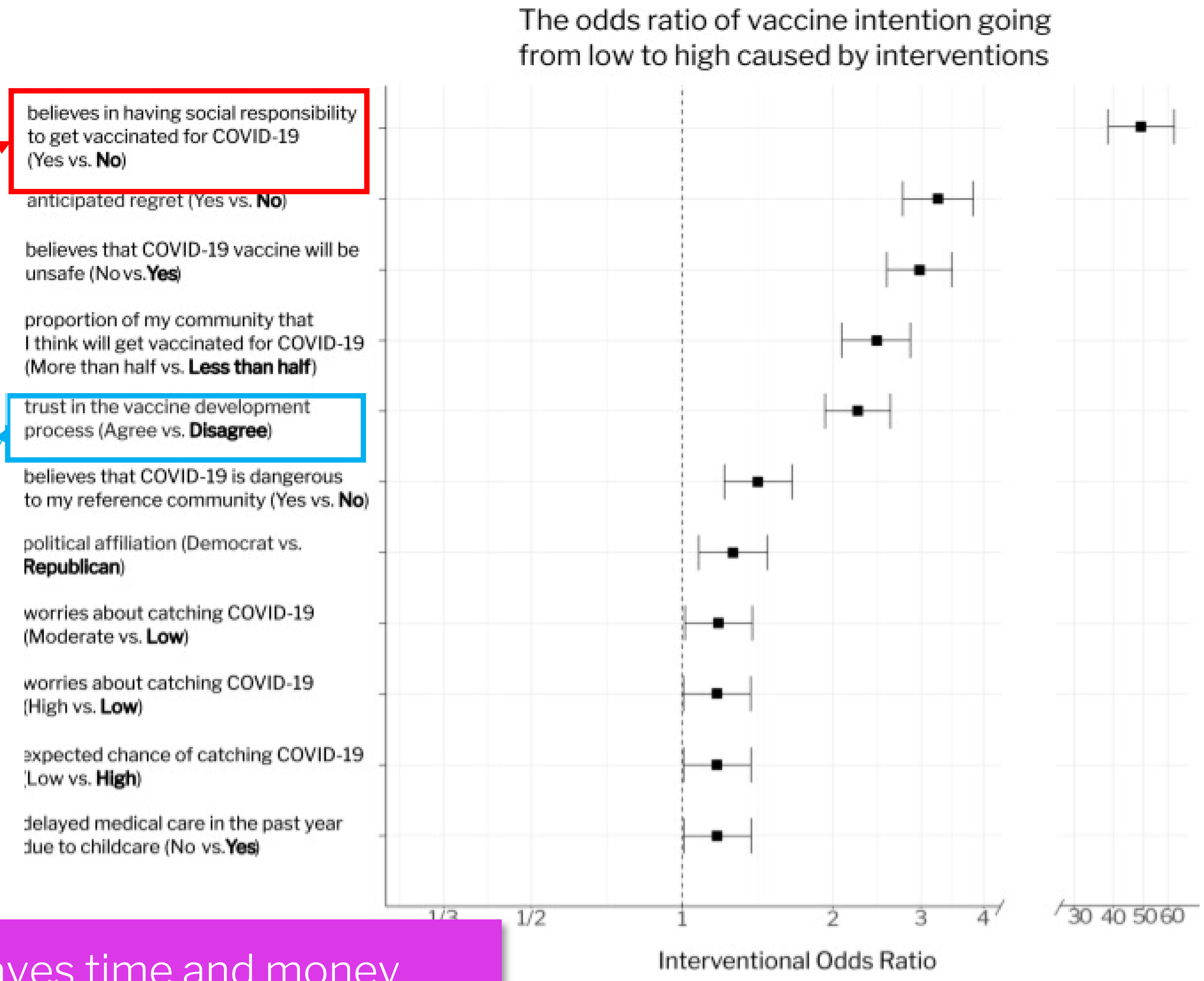


“cutting” *all* directed edges toward X

Koller and Friedman (2009) Probabilistic Graphical Models: Principles and Techniques

Causal Inf Advantage → Multiple treatment candidates →multiple vRCTs!





Easily scalable, saves time and money

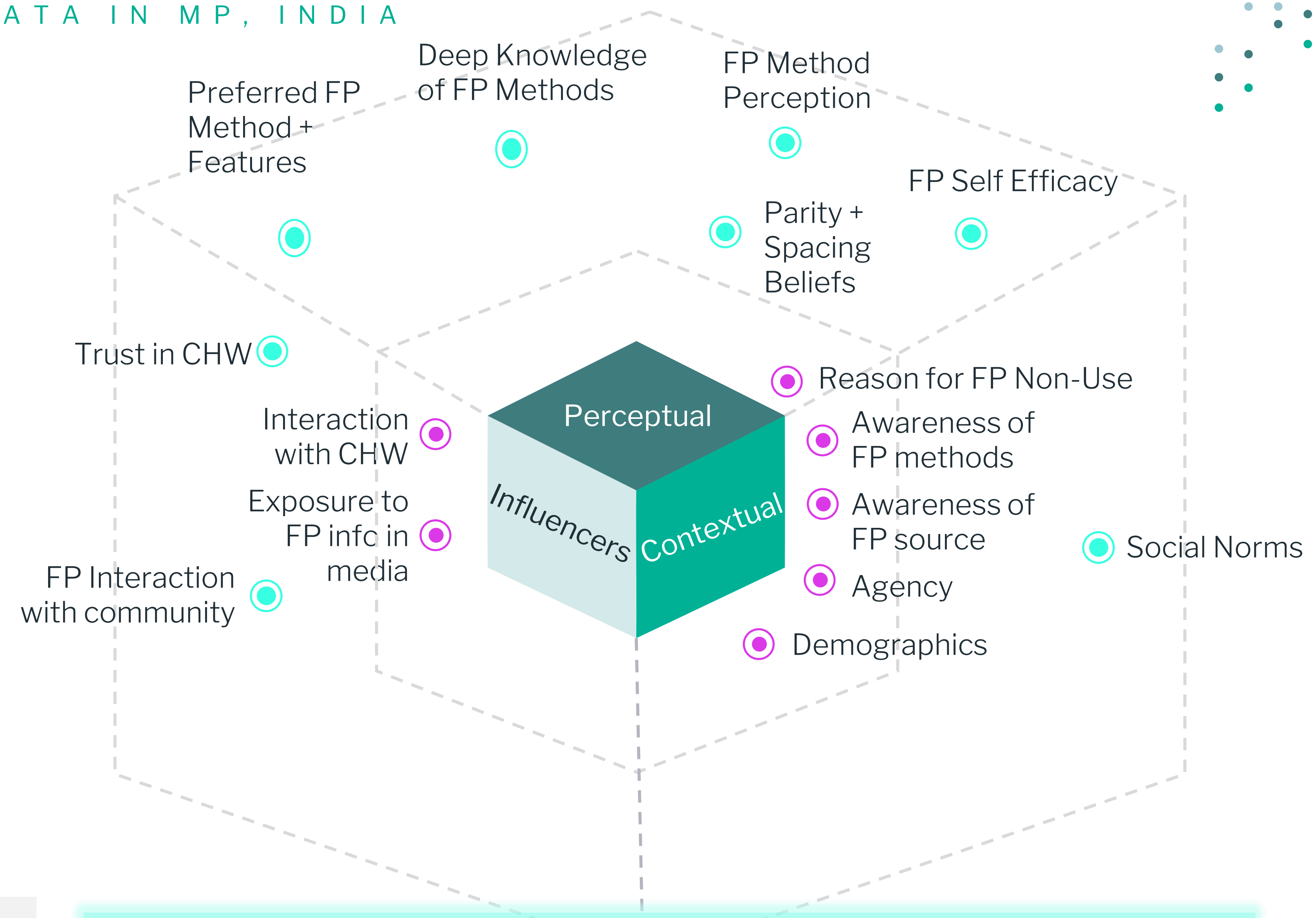
Fung et al 2023

Assumption

All the common causes are in the data

Assumption Failure Mitigation

Thoughtful comprehensive variable (CUBES™)



- State & district representative survey
- 16,105 18-39 years old married women, 5125 husbands, 1409 CHWs interviewed

Our novel dataset is more holistic, contextual, and informed by behavioral science and community dynamics and networks

Causal analysis pinpointed very specific intervention levers to drive contraceptive uptake

Direct causes: Pillars of intervention

Cause of causes: Defines interventions

Right messenger: CHW

Aware of MET

Receive FP advice from CHW

Receive FP advice after last birth

MET use

Right message: MET safety

Aware of MET

Concern with MET safety

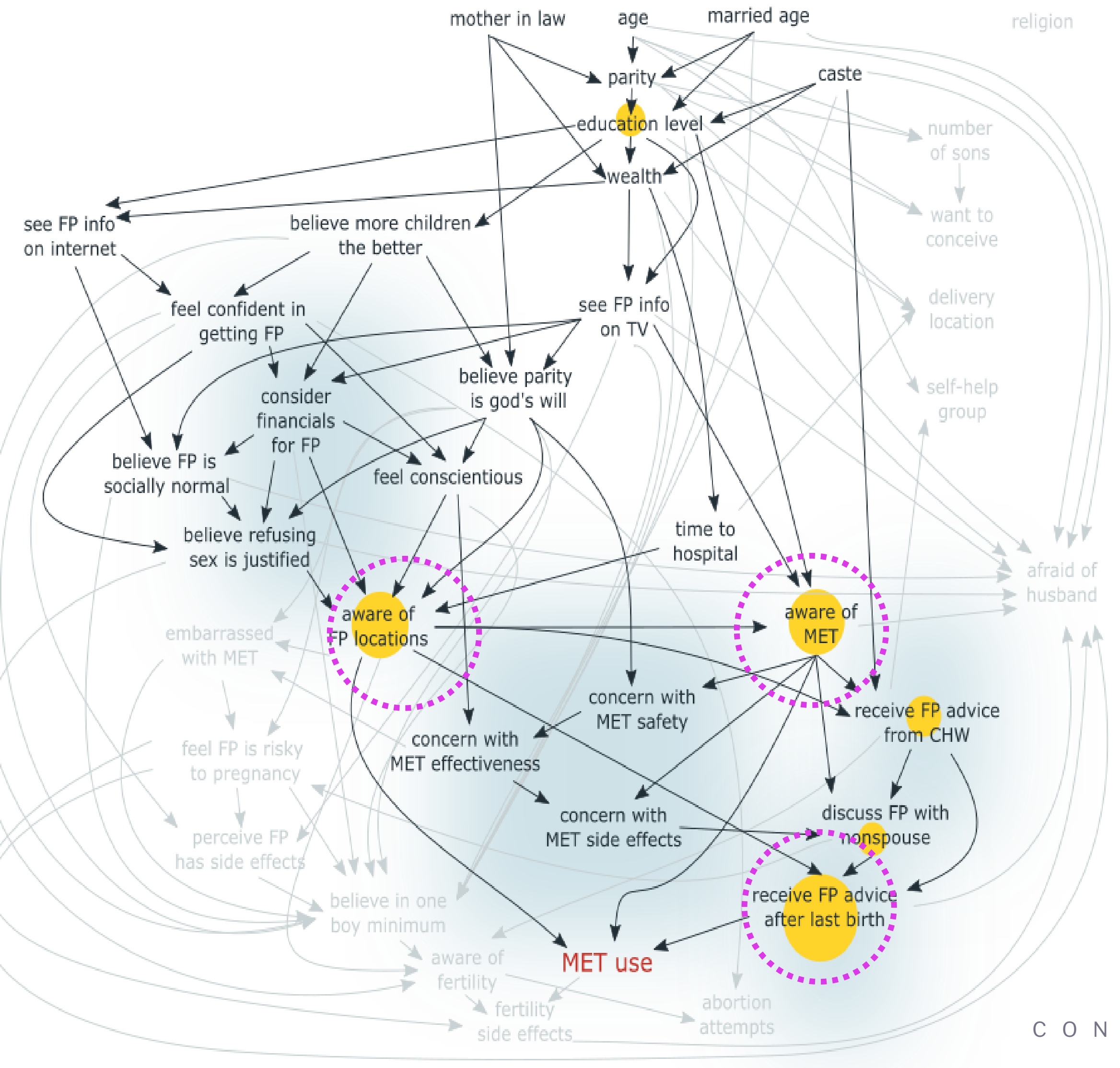
Concern with MET effectiveness

Concern with MET side effects

Discuss FP with non-spouse

Receive FP advice after last birth

MET use



* pills, IUD, injectables

Direct causes for MET use

XYZ → Causal to MET use

XYZ → Not causal to MET use

Significant effects (Odds ratio) for intervention to affect MET use :

3.0
2.0
1.0

More odds of MET use

No difference

Radius reflects influence on MET use

Causal Pathway

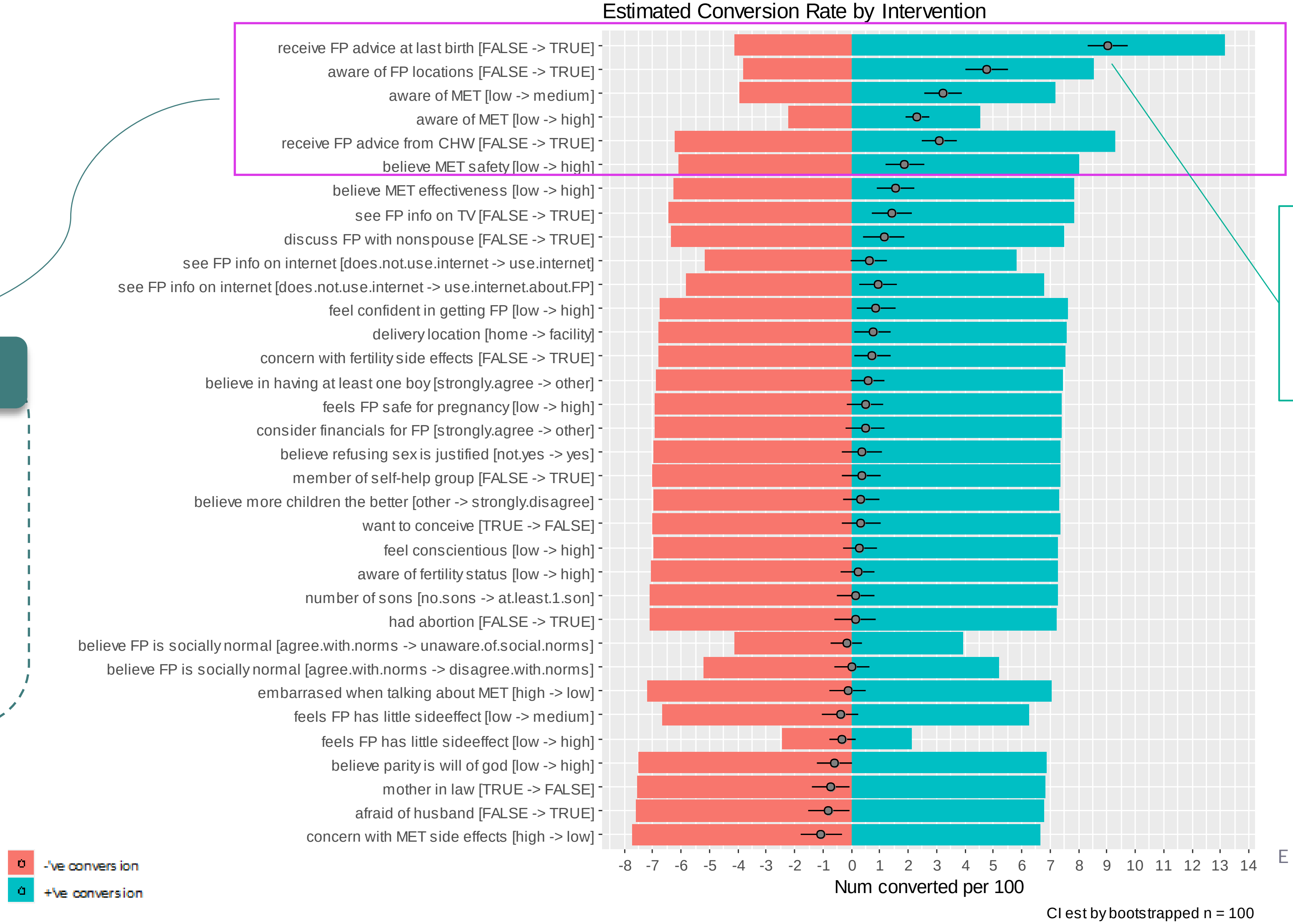
Non-causal

Estimating candidate interventions' net impact pre-deployment - a resource-effective method to select high ROI levers and gave a roadmap for design

Virtual RCT: Prioritize interventions based on estimated impact

High ROI levers

- ❑ Receive postpartum FP advice
- ❑ Aware of FP locations
- ❑ Aware of FP methods
- ❑ Receive FP advice from CHW
- ❑ Believe MET safety

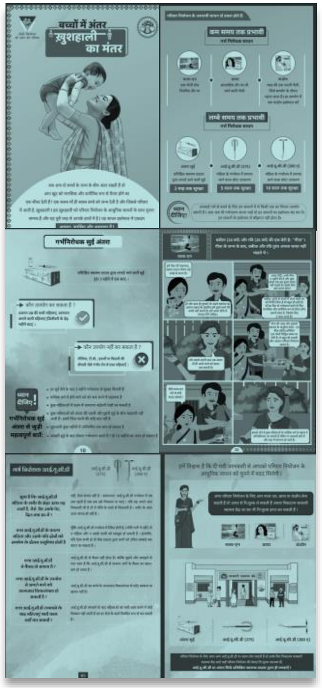


The model estimated ~9 pp increase over control if optimal CHW intervention implemented

Cluster RCT showed significant shifts in intent + 3x uptake

On-ground Intervention Design

Based on **causal insights + participatory design work** with CHWs and women



Size: ~880 post-partum women (3-9 mo) + 220 CHWs /arm

Cluster: CHW catchment areas

Time: Oct 22-Mar 23

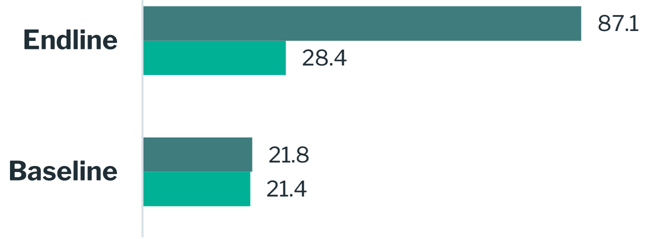
Intervention:

- CHWs made 5 strategically timed visits per woman
- Structured counselling and BCC material in each visit developed based on causal factors

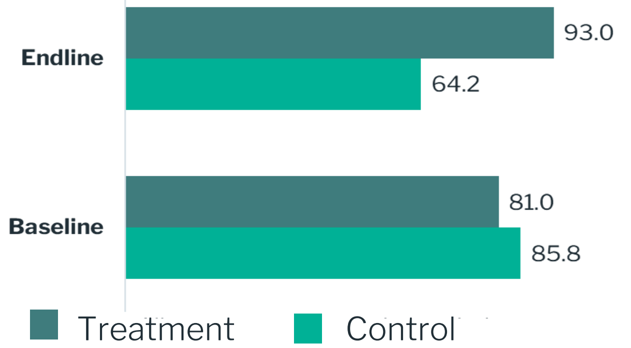
Gains in CHW Activity

Improved role clarity and service delivery tools → led to 10 pp rise in visits but 59 pp shift in discussing FP**; highly scalable**

CHW discussed FP during visit(%)



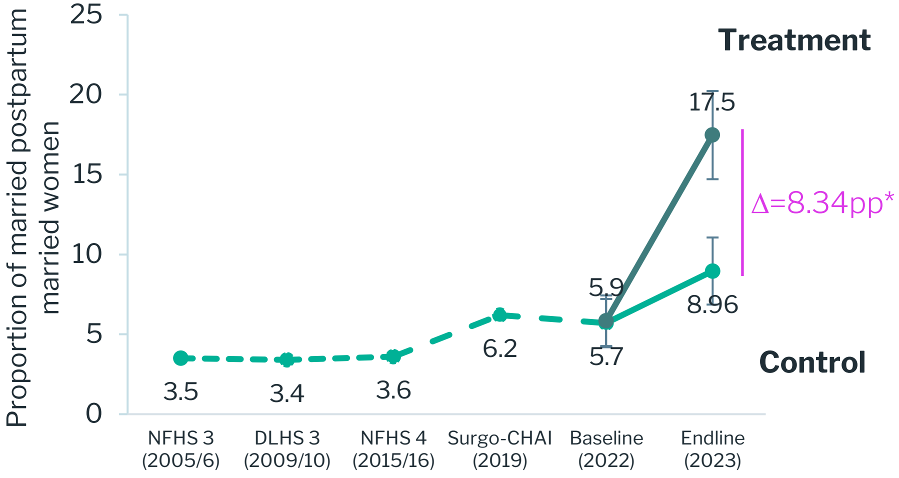
CHW visits over 6 months (%)



Gains in FP Intent and Uptake

FP use saw a jump, 3X from 6 to 18% in the treatment arm. **Intent to use also jumped up by 9 pp**

CURRENT USE (%)
Pills, Injectables, IUD



*With additional adjustment for Difference-in-difference, treatment effect is 7 pp (95%CI: 3-11 pp)

IMPACT

Successful modeling and validation is enabling government scale up of the intervention

Government of Madhya Pradesh (GoMP) is considering scaling up the intervention across all 52 districts - potentially benefitting ~77,000 ASHA workers and over 20 million women in the state

ASHAs self-reported high usability benefits of Info. Edu. Comm. (IEC) while counseling women

Successful award of a grant from UN Population Fund (UNFPA) to CHAI to scale up intervention through technical and implementation assistance to the Government of MP in three focal districts

- The aim of the grant is to increase contraceptive access, and to counsel women on family planning and sexual and reproductive health across three focal districts.

Enabling design and optimization of interventions around priority variables

Pinpoint focused intervention levers

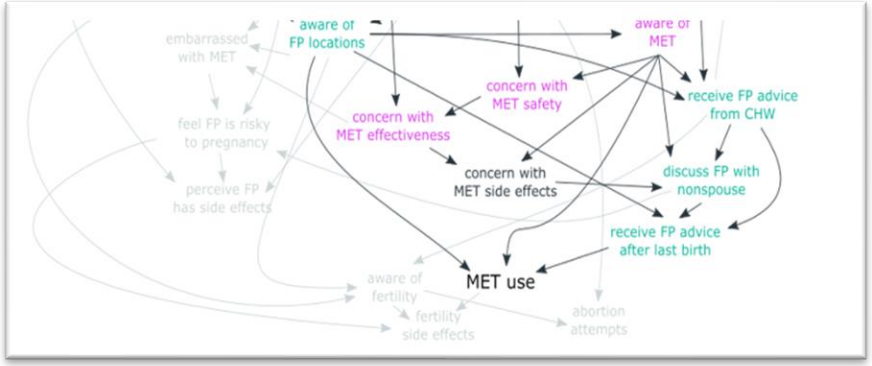
From a complex set of 30-40 candidates, highlight direct causal factors around which to intervene

Guide intervention design via cause of causes

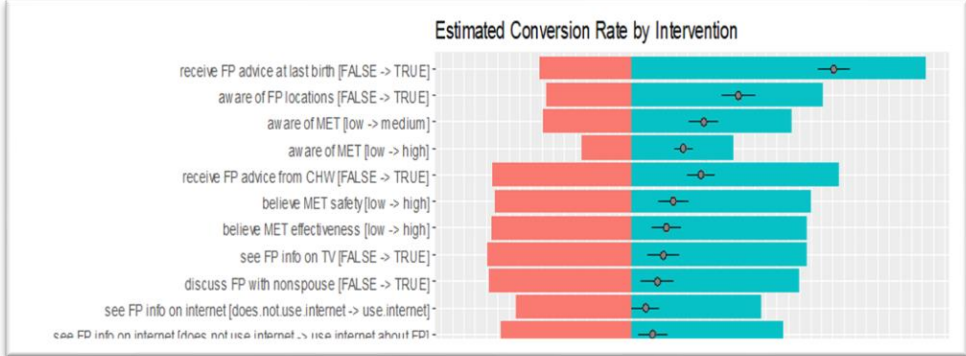
Uncover upstream causal drivers to unlock downstream impact

Direct efficient resource allocation

Simulate RCTs and determine impact of potential interventions (and bundles) leading to time and experimentation cost savings



Use of causal pathways to refine intervention design



Virtual RCTs to identify high impact interventions

Showcase paths to scale: Identify and amplify existing pathways to drive FP uptake at scale in focus countries and regions

We are hiring!

https://surgohealth.pinpointhq.com/

Questions?

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