H1: Consistent Prioritization Decisions
- Of the 179 participants in the no goal group, 94 were in the OO group, 67 were in the VO group, and 8 did not meet criteria for either group.
- 90% of participants were consistent in their decision-making.

H2: Providing predictions leads to OO decision making
- By an almost 2:1 ratio, those with prior exposure to predictions reveal themselves as OO.
- Those without reveal themselves as VO.

H3: Seeing predictions leads to decisions consistent with type
- OO and VO types have similar OO scores when shown just vignettes.
- When shown both vignettes and risk predictions, VO types become more aligned with making VO decisions.
- OO types become more aligned with making OO decisions.

These differences are statistically significant, p-value = 5.4e-1.

Methodology
Mechanical Turk survey with 458 participants:
1. Three tasks:
   - Effect of Training Task
     - Given vignettes categorize households into low, medium, or high probability of reentry if assigned TH.
     - Half given training, half got no training.
   - Effect of Algo-Predictions Task
     - Given two households, which should receive TH.
   - Predictions exacerbate competing priorities

Results
Randomization Group: Outcome-Oriented Vulnerability-Oriented
Training + Vignette Only Group: N = 28 N = 12
Training + Vignette and Predictions Group: N = 22 N = 14
No Training + Vignette Only Group: N = 19 N = 15
No Training + Vignette and Predictions Group: N = 27 N = 18

Three groups:
1. Those who are VO and will remain so regardless of exposure to predictions.
2. Those who are OO and will remain so regardless of exposure.
3. Those who would be VO, but switch to being OO once exposed to information about outcomes.

Conclusion
Predictions exacerbate competing priorities.
- Clashing priorities in the current system.
- Could be exacerbated by the inclusion of an algorithmic decision aid.

Implementation should not be done without additional research.
- Important to understand the morals of introducing these tools.
- Next step: replication of this work with homeless caseworkers.
- Many factors to keep in mind throughout the research pipeline.
- How and when is fairness determined.
- Moral considerations at both the optimization and the implementation levels.
- Reason deliberately about the morals involved in introducing machine learning and AI into decision-making processes.

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References

Data and Prediction
HMIS Data for St. Louis, MO from 2009-2014
- Aggregated across time using data from 75 different agencies.
- Linked with central homeless hotline.
- Contains household characteristics available upon entry.
- Reentry – requesting services within two years of exit from the system, regardless of whether services were received.

Build Bayesian Additive Regression Trees (BART) models based on HMIS data and use them to predict the counterfactual outcomes.

Hypotheses
H1: Decisions primarily fall into two types: outcome- & vulnerability-oriented
H2: Prior exposure to predictions introduces a goal-framing effect, leading to more outcome-oriented future allocation decisions.
H3: Without defined allocation goals, the presentation of algorithmic predictions reveals prioritization types of decision-makers.

Introduction
Local Justice Problem: Who should be prioritized for receipt of a scarce resource?
- Outcome-oriented vs Vulnerability-oriented

How does seeing these predictions affect decision-making?