Just Resource Allocation? How Algorithmic Predictions and Human Notions of Justice Interact

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Introduction

Local Justice Problem: Who should be prioritized for receipt of a scarce resource?

- Outcome-oriented vs Vulnerability-oriented

How does providing predictions interact with decision-maker priorities and institution goals?

Context: Allocating scarce homeless services

- Scarce Resource: Transitional Housing – intensive and costly, provides stable housing as well as supportive services for extended period
- Baseline Resource: Emergency Shelter – less intensive and costly, provides immediate form of shelter for a short time
- Outcome-Oriented - give transitional housing to the household that will have the lowest risk if
- Vulnerability-Oriented – give transition housing to the household that will have the highest probability of reentry

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

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

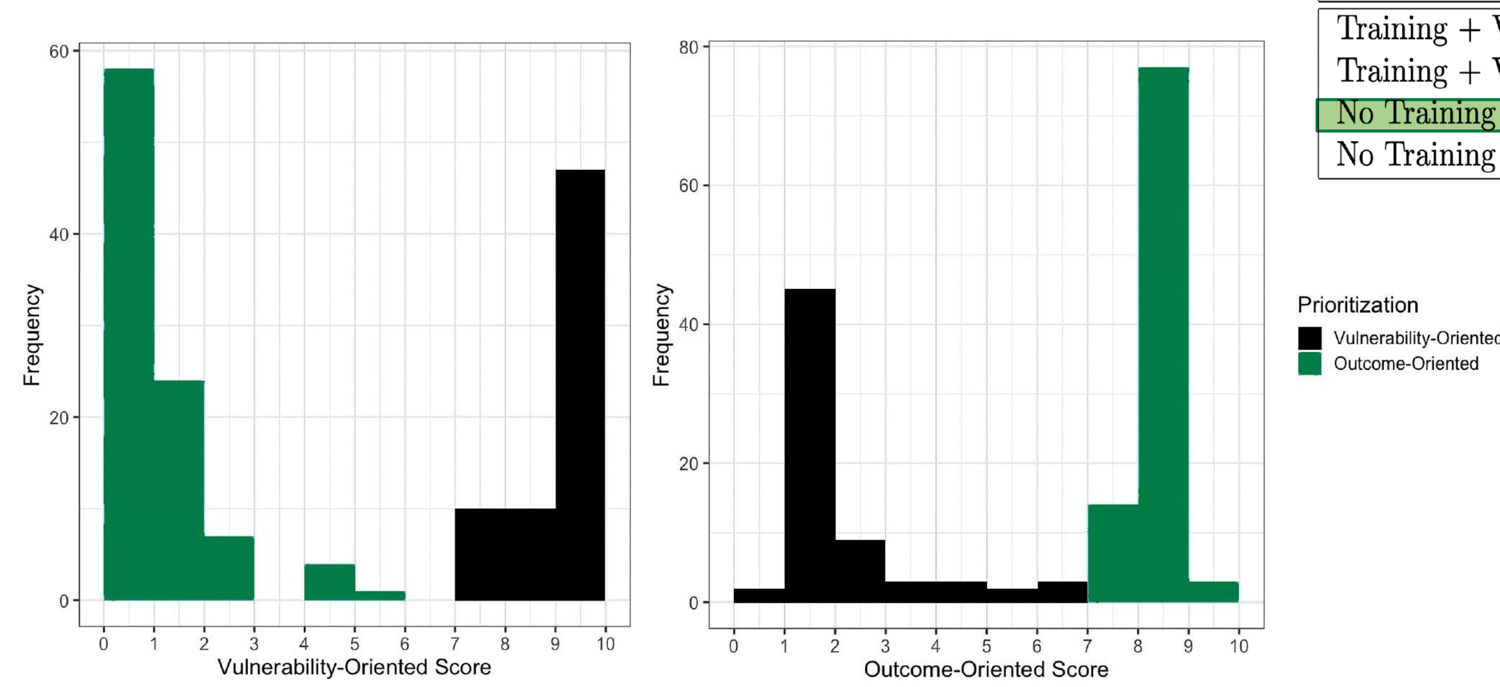
How does seeing these predictions affect decision-making?

	Rapid Rehousing	Emergency Shelter	Transitional Housing	Homelessness Prevention
	P^A_{RRH}	P^A_{ES}	P^A_{TH}	P^A_{Prev}
	P^B_{RRH}	P^B_{ES}	P^B_{TH}	P^B_{Prev}
	P^C_{RRH}	P^C_{ES}	P^C_{TH}	P^C_{Prev}

Results

H1: Consistent Prioritization Decisions

- Of the 179 participants in the no goal group
  - 94 were in the the OO group,
  - 67 were in the VO group,
  - 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

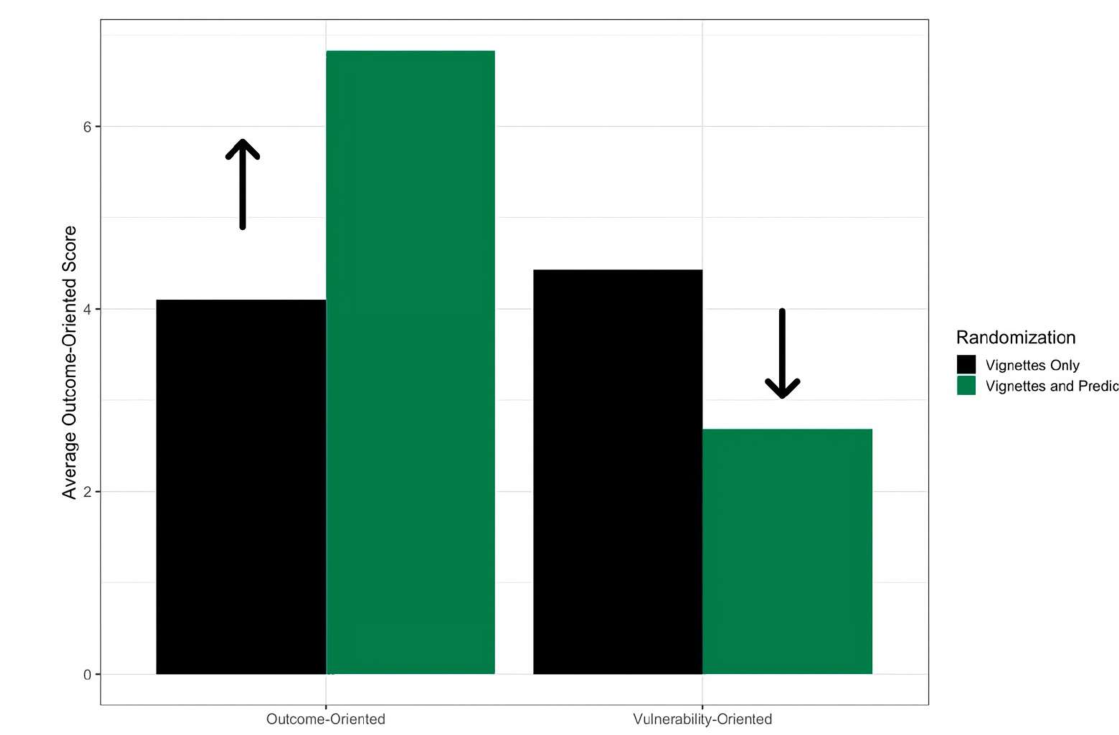
Randomization Group	*Outcome-Oriented*	*Vulnerability-Oriented*
Training + Vignette Only Group	$N = 28$	$N = 12$
Training + Vignette and Predictions Group	$N = 27$	$N = 14$
No Training + Vignette Only Group	$N = 12$	$N = 23$
No Training + Vignette and Predictions Group	$N = 27$	$N = 18$

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.

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 = 5.04e-1



Methodology

Mechanical Turk survey with 458 participants -Three tasks:

1. **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

	Household 1	Household 2	Household 3	Household 4	Household 5	Household 6	Household 7	Household 8	Household 9	Household 10
Number of Household Members	1	1	1	1	1	1	1	1	1	1
Number of Children	0	0	0	0	0	0	0	0	0	0
Head of Household Gender	Male	Male	Female	Male	Female	Male	Male	Male	Male	Male
Head of Household Age	35	45	35	45	45	45	55	45	45	35
Head of Household Disabling Condition	Yes	Yes	No	No	No	Yes	No	Yes	No	No
Head of Household Receives Substance Abuse Services	Yes	No	No	No	Yes	Yes	No	Yes	Yes	No
Monthly Income	$400	$1524	$668	$200	$800	$668	$0	$0	$200	$0
Number of Calls to Hotline	5	1	15	25	1	3	25	5	2	25
Prior Residence	Private Emergency Shelter	Place not meant for habitation	Permanent housing for formerly homeless persons	Private Emergency Shelter	Place not meant for habitation	Private Emergency Shelter	Private Emergency Shelter	Place not meant for habitation	Private Emergency Shelter	Private Emergency Shelter

High probability of future need in Transitional Housing | Medium probability of future need in Transitional Housing | Low probability of future need in Transitional Housing

Household 1 Household 2 Household 3 Household 4 Household 5 Household 6 Household 7 Household 8 Household 9 Household 10

2. **Effect of Algo-Predictions Task**
   - Given two households, which should receive TH
   - Half given vignettes, half given vignettes + predictions
   - Decisions consistent with outcome-oriented approach add +1 to outcome-oriented (OO) score
   - Decisions consistent with vulnerability-oriented approach add +1 to vulnerability-oriented (VO) score

	Household 1	Household 2
Number of Household Members	1	1
Number of Children	0	0
Head of Household Gender	Female	Male
Head of Household Age	55	35
Head of Household Disabling Condition	Yes	No
Head of Household Receives Substance Abuse Services	No	Yes
Monthly Income	$0	$0
Number of Calls to Hotline	5	2
Prior Residence	Private Emergency Shelter	Private Emergency Shelter
Predicted probability of needing future services within 2 years if given Transitional Housing	High	Low
Predicted probability of needing future services within 2 years if given Emergency Shelter	High	Medium

	Household 1	Household 2
Number of Household Members	1	1
Number of Children	0	0
Head of Household Gender	Female	Female
Head of Household Age	35	45
Head of Household Disabling Condition	No	No
Head of Household Receives Substance Abuse Services	No	Yes
Monthly Income	$668	$800
Number of Calls to Hotline	15	1
Prior Residence	Permanent housing for formerly homeless persons	Place not meant for habitation

3. **Type Elicitation Task**
   - Given only predictions which should receive TH
   - One third OO, one third VO, one third no goal
   - Participants with OO score >= 7 are considered OO Type
   - Participants with VO score >= 7 are considered OO Type

	Household 1	Household 2
Predicted probability of needing future services within 2 years if given Transitional Housing	Low	Medium
Predicted probability of needing future services within 2 years if given Emergency Shelter	High	High

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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