

Does AI help humans make better decisions?

A statistical evaluation framework for experimental
and observational studies

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Distinguished Lecture

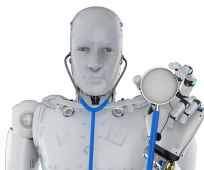
Mannheim Center for Data Science

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Joint work with Eli Ben-Michael, D. James Greiner, Melody Huang,
Zhichao Jiang, and Sooahn Shin

AI-assisted (Algorithm-assisted) human decision making

- AI and data-driven algorithms are everywhere in our daily lives
- But, humans still make many consequential decisions
- We have not yet outsourced high-stakes decisions to AI



- this is true even when human decisions can be suboptimal
 - we may want to hold *someone*, rather than *something*, accountable
- Most prevalent system is **AI-assisted human decision making**
 - humans make decisions with the aid of AI recommendations
 - routine decisions made by individuals in daily lives
 - consequential decisions made by doctors, judges, etc.

Key questions and contributions

- How do AI recommendations influence human decisions?
 - Does AI help humans make more accurate decisions?
 - Does AI help humans improve the fairness of their decisions?
- Many have studied the accuracy and fairness of AI recommendations
 - Relatively few have researched their impacts on human decisions
 - Little is known about how AI's bias interacts with human bias
- A statistical evaluation framework for AI recommendations
 - ① **experimental studies**: randomize human-alone vs. human+AI decisions
 - ② **observational studies**: also applicable under unconfoundedness
 - ③ **methodology**:
 - compare human-alone, human+AI, and AI-alone
 - optimally combine human decisions with AI recommendations
 - ④ **first ever field experiment**: evaluating pretrial public safety assessment

Pretrial public safety assessment (PSA)

- AI recommendations often used in US criminal justice system
- At the **first appearance hearing**, judges primarily make two decisions
 - 1 whether to release an arrestee pending disposition of criminal charges
 - 2 what conditions (e.g., bail and monitoring) to impose if released
- Goal: avoid predispositional incarceration while preserving public safety
- Judges are required to consider three risk factors along with others
 - 1 arrestee may fail to appear in court (FTA)
 - 2 arrestee may engage in new criminal activity (NCA)
 - 3 arrestee may engage in new violent criminal activity (NVCA)
- **PSA** as an AI recommendation to judges
 - classifying arrestees according to FTA and NCA/NVCA risks
 - derived from an application of a machine learning algorithm to a training data set based on past observations
 - used in more than 25 states

Field experiment for evaluating the PSA

- Dane County, Wisconsin
- PSA = weighted indices of ten factors
 - age as the single demographic factor: no gender or race
 - nine factors drawn from criminal history (prior convictions and FTA)
- **PSA scores and recommendation** [▶▶ PSA details](#)
 - ① two separate ordinal six-point risk scores for FTA and NCA
 - ② one binary risk score for new violent criminal activity (NVCA)
 - ③ aggregate recommendation: signature bond, small and large cash bail
- Judges may have other information about an arrestee
 - affidavit by a police officer about the arrest
 - defense attorney may inform about the arrestee's connections to the community (e.g., family, employment)
- **Field experiment**
 - PSA is calculated for each case using a computer system
 - provision of PSA is randomized across cases
 - mid-2017 – 2019 (randomization), 2-year follow-up for half sample
 - we have made the data set publicly available!



DANE COUNTY CLERK OF COURTS

Public Safety Assessment – Report

215 S Hamilton St #1000
Madison, WI 53703
Phone: (608) 266-4311

Name: [REDACTED]

Spillman Name Number: [REDACTED]

DOB: [REDACTED]

Gender: Male

Arrest Date: 03/25/2017

PSA Completion Date: 03/27/2017

New Violent Criminal Activity Flag

No

New Criminal Activity Scale

1	2	3	4	5	6
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Failure to Appear Scale

1	2	3	4	5	6
---	---	---	---	---	---

Charge(s):

961.41(1)(D)(1) MFC DELIVER HEROIN <3 GMS F 3

Risk Factors:

Responses:

1. Age at Current Arrest	23 or Older
2. Current Violent Offense	No
a. Current Violent Offense & 20 Years Old or Younger	No
3. Pending Charge at the Time of the Offense	No
4. Prior Misdemeanor Conviction	Yes
5. Prior Felony Conviction	Yes
a. Prior Conviction	Yes
6. Prior Violent Conviction	2
7. Prior Failure to Appear Pretrial in Past 2 Years	0
8. Prior Failure to Appear Pretrial Older than 2 Years	Yes
9. Prior Sentence to Incarceration	Yes

Recommendations:

Release Recommendation - Signature bond

Conditions - Report to and comply with pretrial supervision

Does the judge agree with PSA?

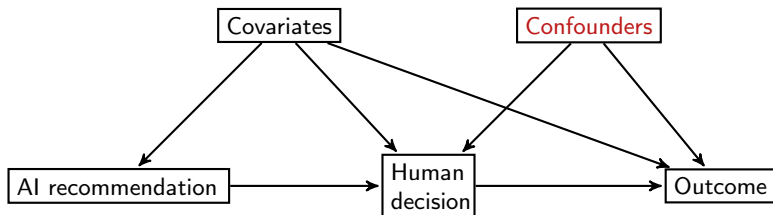
		PSA	
		Signature bond	Cash bail
Human	Signature bond	54.1% (510)	20.7 (195)
	Cash bail	9.4 (89)	15.8 (149)

		PSA	
		Signature bond	Cash bail
Human+PSA	Signature bond	57.3% (543)	17.1 (162)
	Cash bail	7.4 (70)	18.2 (173)

- PSA statistically significantly influence the judge's decision
- But how?

Experimental design

- Two key design features about treatment assignment:
 - 1 **randomization** (strong ignorability): human-alone vs. human+AI
 - 2 **single blinded treatment**: AI recommendations affect the outcome only through human decisions
- The proposed design is widely applicable even when stakes are high



Required assumptions

- Notation

- AI recommendation provision (PSA or not): $Z_i \in \{0, 1\}$
- Human decision (signature bond vs. cash bail): $D_i \in \{0, 1\}$
- Observed outcome (FTA, NCA, or NVCA): $Y_i \in \{0, 1\}$
- Potential decisions and outcomes: $D_i(z), Y_i(z, D_i(z))$

- Assumptions

- ① Single-blinded treatment:

$$Y_i(z, D_i(z)) = Y_i(D_i(z)) \quad \text{for all } i \text{ and } z = 0, 1$$

- ② Unconfounded treatment:

$$Z_i \perp\!\!\!\perp \{A_i, D_i(0), D_i(1), Y_i(0), Y_i(1)\} \mid X_i \quad \text{for all } i$$

- ③ Overlap: $0 < \Pr(Z_i = 1 \mid X_i = x) < 1$ for all x

- These assumptions can be guaranteed by the experimental design
- No other assumptions are required

Classification ability of decision-making system

		Decision	
		Negative ($D^* = 0$)	Positive ($D^* = 1$)
Outcome	Negative ($Y(0) = 0$)	True Negative (TN)	False Positive (FP)
	Positive ($Y(0) = 1$)	False Negative (FN)	True Positive (TP)

- (Generic) Decision D^*
 - Positive: cash bail
 - Negative: signature bond
- Outcome under release $Y(0)$
 - Positive: NCA
 - Negative: no NCA
- Classification ability measures
 - False Positive (FP): unnecessary cash bail
 - False Negative (FN): signature bond followed by NCA
- We focus on $Y(0)$ and ignore $Y(1)$

Classification risk

Outcome	Decision						
	Negative ($D^* = 0$)	Positive ($D^* = 1$)					
	<table><tr><td>Negative ($Y(0) = 0$)</td><td>True Negative (TN) ℓ_{00}</td><td>False Positive (FP) ℓ_{01}</td></tr><tr><td>Positive ($Y(0) = 1$)</td><td>False Negative (FN) $\ell_{10} = 1$</td><td>True Positive (TP) ℓ_{11}</td></tr></table>	Negative ($Y(0) = 0$)	True Negative (TN) ℓ_{00}	False Positive (FP) ℓ_{01}	Positive ($Y(0) = 1$)	False Negative (FN) $\ell_{10} = 1$	True Positive (TP) ℓ_{11}
Negative ($Y(0) = 0$)	True Negative (TN) ℓ_{00}	False Positive (FP) ℓ_{01}					
Positive ($Y(0) = 1$)	False Negative (FN) $\ell_{10} = 1$	True Positive (TP) ℓ_{11}					

- Assign a (possibly asymmetric) 'loss' to each classification outcome
- Classification risk** of decision-making system D^*

$$R(\ell_{01}; D^*) := \underbrace{\ell_{10}}_{=1} \cdot \underbrace{p_{10}(D^*)}_{\text{FNP}} + \ell_{01} \cdot \underbrace{p_{01}(D^*)}_{\text{FPP}},$$

where $p_{yd}(D^*) = \Pr(Y(0) = y, D^* = d)$ for $y, d \in \{0, 1\}$

- misclassification rate**: $R(1; D^*) = \text{FNP} + \text{FPP}$

Comparing human decisions with and without AI

- Risk difference:

$$\begin{aligned} & R_{\text{human+AI}}(\ell_{01}) - R_{\text{human}}(\ell_{01}) \\ &= \{p_{10}(D(1)) - p_{10}(D(0))\} + \ell_{01}\{p_{01}(D(1)) - p_{01}(D(0))\} \end{aligned}$$

- **Selective labels problem**: we do not observe $Y(0)$ when $D = 1$
- FNP is identifiable but FPP is **unidentified**
- The difference of FPP is identifiable
 - by randomization
 $\Pr(Y(0) = 0 \mid Z = 1, X = x) = \Pr(Y(0) = 0 \mid Z = 0, X = x)$
 - by law of total probability

$$\begin{aligned} & p_{01}(D(1) \mid X = x) + p_{00}(D(1) \mid X = x) \\ &= p_{01}(D(0) \mid X = x) + p_{00}(D(0) \mid X = x) \end{aligned}$$

Doubly robust estimation

- Identification formula:

$$\begin{aligned} & R_{\text{human+AI}}(\ell_{01}) - R_{\text{human}}(\ell_{01}) \\ &= \mathbb{E} [\Pr(Y = 1, D = 0 \mid Z = 1, X) - \Pr(Y = 1, D = 0 \mid Z = 0, X) \\ &\quad - \ell_{01} \{ \Pr(Y = 0, D = 0 \mid Z = 1, X) - \Pr(Y = 0, D = 0 \mid Z = 0, X) \}] \end{aligned}$$

- Compound outcome: $W_i := Y_i(1 - D_i) - \ell_{01}(1 - Y_i)(1 - D_i)$
- Three models:
 - 1 propensity score: $e(z, x) := \Pr(Z = z \mid X = x)$
 - 2 decision model: $m^D(z, x) := \Pr(D = 1 \mid Z = z, X = x)$
 - 3 outcome model: $m^Y(z, x) := \Pr(Y = 1 \mid D = 0, Z = z, X = x)$

- AIPW estimator:

$$\hat{\beta} = \frac{1}{n} \sum_{i=1}^n \{ \hat{\varphi}_1(Z_i, X_i, D_i, Y_i; \ell_{01}) - \hat{\varphi}_0(Z_i, X_i, D_i, Y_i; \ell_{01}) \}$$

where $\hat{\varphi}_z(Z, X, D, Y; \ell_{01})$ is the (uncentered) influence function:

$$\begin{aligned} & \hat{\varphi}_z(Z, X, D, Y; \ell_{01}) \\ &:= (1 - \hat{m}^D(z, X)) \{ (1 + \ell_{01}) \hat{m}^Y(z, X) - \ell_{01} \} \\ & \quad + (1 + \ell_{01}) \frac{\mathbb{1}\{Z = z\}(1 - D)}{\hat{e}(z, X)} (Y - \hat{m}^Y(z, X)) \\ & \quad - \{ (1 + \ell_{01}) \hat{m}^Y(z, X) - \ell_{01} \} \frac{\mathbb{1}\{Z = z\}}{\hat{e}(z, X)} (D - \hat{m}^D(z, X)) \end{aligned}$$

- Properties:
 - asymptotic normality
 - double robustness: (outcome model + decision model) $\times$ propensity score model

When do you prefer human-alone vs. human+AI?

- Hypothesis test given the relative loss ℓ_{01} :

$$H_0 : R_{\text{Human}}(\ell_{01}) \leq R_{\text{Human+AI}}(\ell_{01}),$$

$$H_1 : R_{\text{Human}}(\ell_{01}) > R_{\text{Human+AI}}(\ell_{01})$$

- Invert this test to obtain a confidence interval on ℓ_{01}
 - 1 Reject H_0 : prefer Human+AI over Human-alone
 - 2 Reject H_1 : prefer Human-alone over Human+AI
 - 3 Fail to reject either hypothesis: statistically ambiguous

Comparing AI decisions with human-alone and human+AI

- What happens if we completely outsource decisions to AI?
- No experimental arm for AI-alone decision system

$$R_{\text{AI}}(\ell_{01}) := R(\ell_{01}; A) = p_{10}(A) + \ell_{01}p_{01}(A)$$

where

$$p_{ya}(A) = \Pr(Y(0) = y, A = a, D = 1) + \Pr(Y(0) = y, A = a, D = 0)$$

- Derive the sharp bound of risk difference: e.g., $R_{\text{AI}}(\ell_{01}) - R_{\text{Human}}(\ell_{01})$
- The bound width depends on the agreement between Human and AI:

$$(1 + \ell_{01}) \mathbb{E} \left\{ \Pr(A = 0 \mid X) - \max_{z'} \Pr(Y = 1, D = 0, A = 0 \mid Z = z', X) \right. \\ \left. - \max_{z'} \Pr(Y = 0, D = 0, A = 0 \mid Z = z', X) \right\}$$

- Applicable to **any generic AI** or any other decision system

Doubly robust estimation

- Estimation of bounds is complex
 - ① data-driven choice of z'
 - ② estimation of the bounds given the optimal choice of z'

- Decision and outcome models:

- ① $m^D(z, x, a) := \Pr(D = 1 \mid Z = z, X = x, A = a)$
- ② $m^Y(z, x, a) := \Pr(Y = 1 \mid D = 0, Z = z, X = x, A = a)$

- Nuisance classifier for the lower bound:

$$g_{L_z}(x) = \mathbb{1}\{(1 - m^D(1 - z, x, 0))m^Y(1 - z, x, 0) \geq (1 - m^D(z, x, 0))m^Y(z, x, 0)\}$$

- assume that this nuisance classifier is well separated
 - plug-in estimation
- Compound outcomes: $Y(1 - D)(1 - A)$, $(1 - Y)(1 - D)(1 - A)$, $(1 - A)D$, and $A(1 - D)$
- AIPW: asymptotic normality, double-robustness

When do you prefer Ai-alone vs. Human-alone?

- Same hypothesis testing framework as before:

$$H_0 : R_{\text{AI}}(\ell_{01}) \leq R_{\text{Human}}(\ell_{01}),$$

$$H_1 : R_{\text{AI}}(\ell_{01}) > R_{\text{Human}}(\ell_{01}).$$

- Due to partial identification, we instead test

- 1 $H_{L0} : L_0 \leq 0$ vs. $H_{L1} : L_0 > 0$

- 2 $H_{U0} : U_0 \geq 0$ vs. $H_{U1} : U_0 < 0$

- As before, we invert these hypothesis tests

- 1 Rejecting H_{L0} implies Human is preferred over AI

- 2 Rejecting H_{U0} implies AI is preferred over Human

- 3 Ambiguous otherwise

Learning when to provide AI recommendations

- Policy: $\pi : \mathcal{X} \rightarrow \{0, 1\}$, provide AI recommendation or not
- Optimal policy:

$$\pi_{\text{rec}}^* \in \operatorname{argmin}_{\pi \in \Pi} \underbrace{p_{10}(D(\pi(X))) + \ell_{01} p_{01}(D(\pi(X)))}_{=R_{\text{rec}}(\ell_{01}; \pi)}$$

where

$$\begin{aligned} & R_{\text{rec}}(\ell_{01}; \pi) \\ &= R_{\text{human}}(\ell_{01}) + \mathbb{E}[\pi(X) \{p_{10}(D(1) | X) - p_{10}(D(0) | X) \\ &\quad - \ell_{01} \cdot (p_{00}(D(1) | X) - p_{00}(D(0) | X))\}] \end{aligned}$$

- Empirical risk minimization using the doubly robust score

Learning when to follow AI recommendations

- Optimally following the AI recommendations (when we know the AI-alone system is better than the human decision-maker):

$$\pi_{\text{dec}}^* \in \operatorname{argmin}_{\pi \in \Pi} p_{10}(\tilde{D}(\pi(X))) + \ell_{01} p_{01}(\tilde{D}(\pi(X))),$$

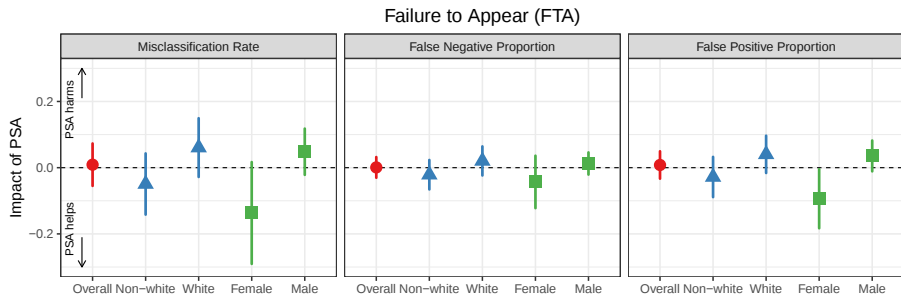
where $\tilde{D}(\pi(X)) = A\pi(X) + D(0)(1 - \pi(X))$

$$\begin{aligned} R_{\text{dec}}(\ell_{01}; \pi) \\ = R_{\text{human}}(\ell_{01}) + \mathbb{E}[\pi(X) \{p_{10}(A | X) - p_{10}(D(0) | X) \\ + \ell_{01} \cdot (p_{01}(A | X) - p_{01}(D(0) | X))\}] \end{aligned}$$

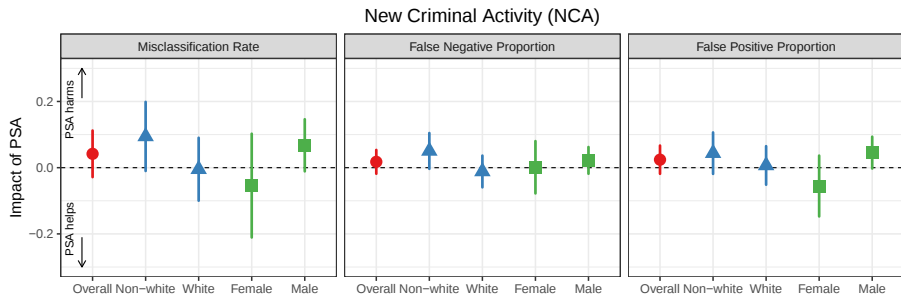
- Use the partial identification and doubly-robust score to optimize the empirical **worst-case risk** (upper bound) $\rightsquigarrow$ safe policy learning

$$\pi_{\text{dec}}^* \in \operatorname{argmin}_{\pi \in \Pi} \mathbb{E}[\pi(X) U_0(X)],$$

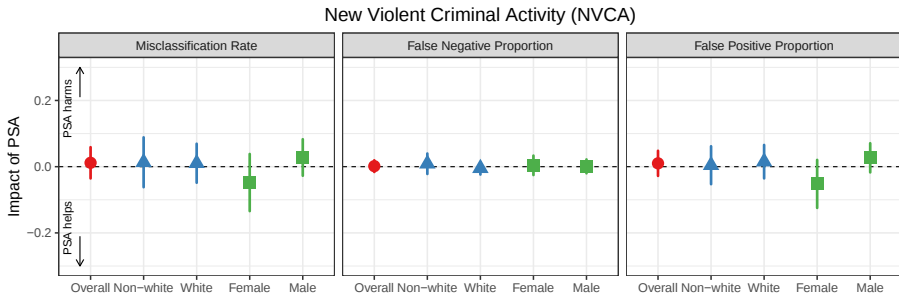
PSA recommendations do not improve human decisions



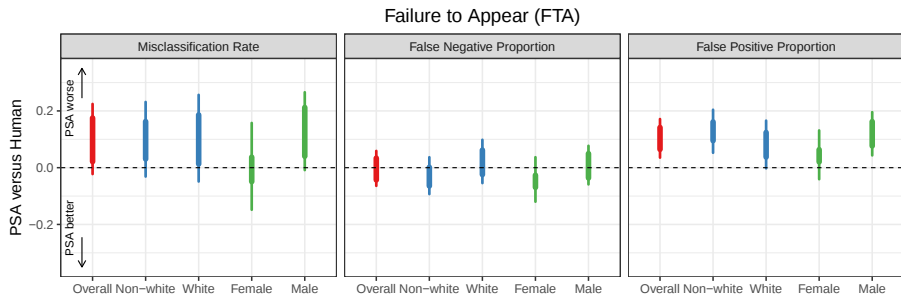
PSA recommendations do not improve human decisions



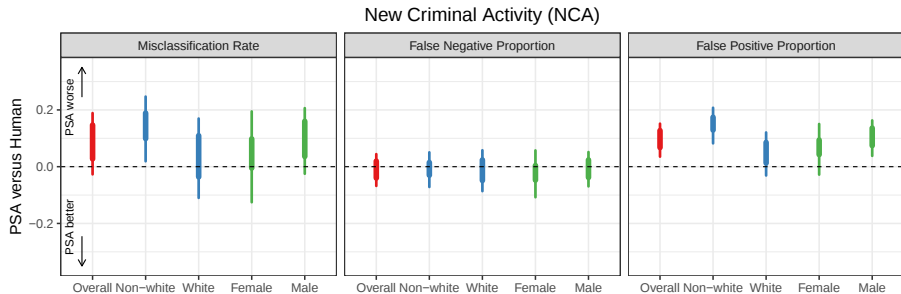
PSA recommendations do not improve human decisions



PSA-alone decisions are less accurate than human decisions

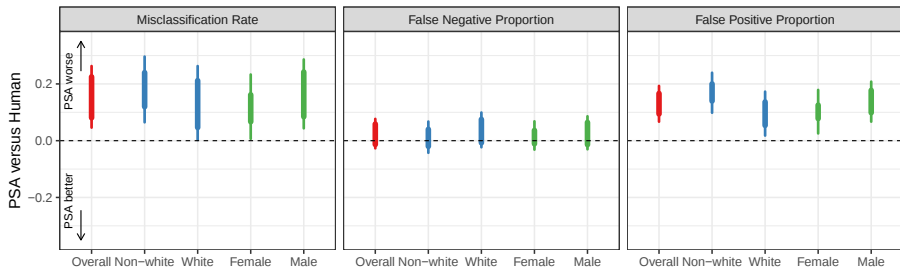


PSA-alone decisions are less accurate than human decisions

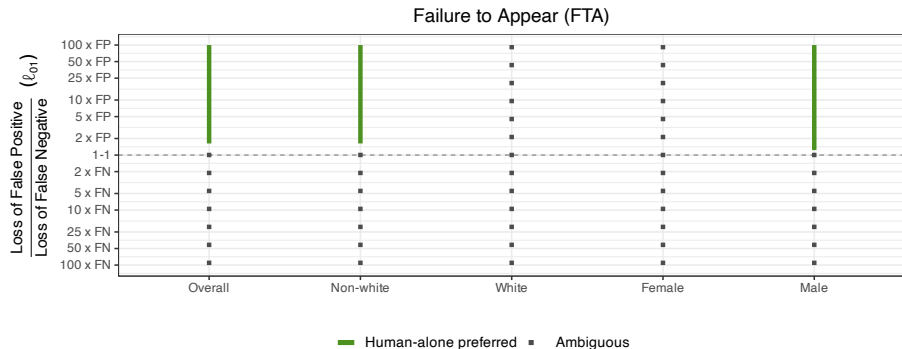


PSA-alone decisions are less accurate than human decisions

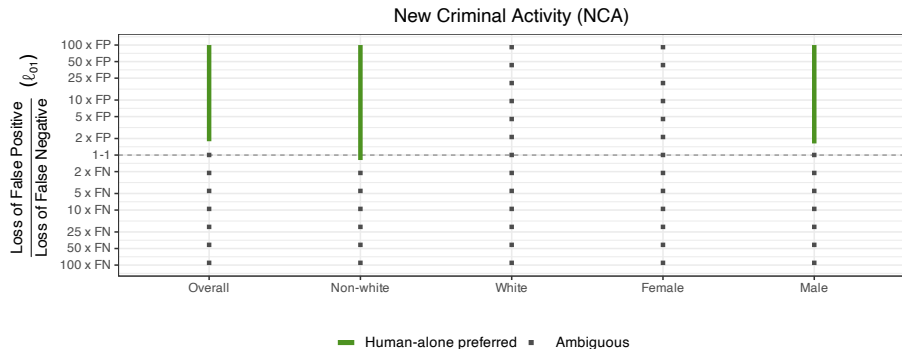
New Violent Criminal Activity (NVCA)



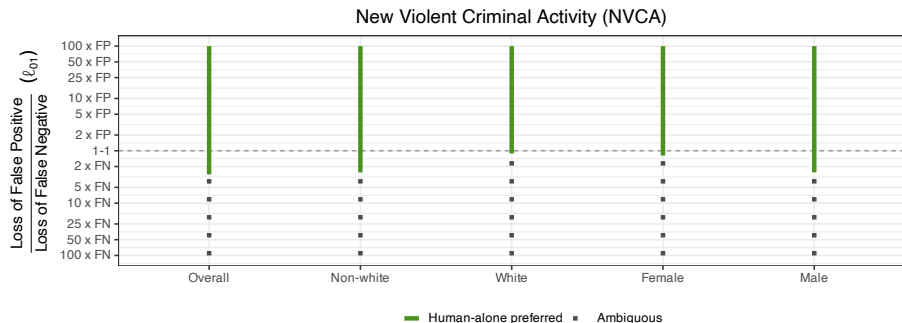
Human-alone system is preferred over PSA-alone system
when the cost of false positive is high



Human-alone system is preferred over AI-alone system when the cost of false positive is high

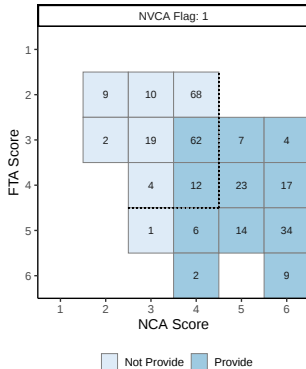


Human-alone system is preferred over AI-alone system when the cost of false positive is high

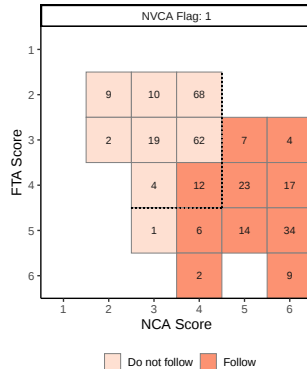


Optimally combining PSA recommendations with human decisions

Whether to provide PSA recommendations



Whether to follow PSA recommendations



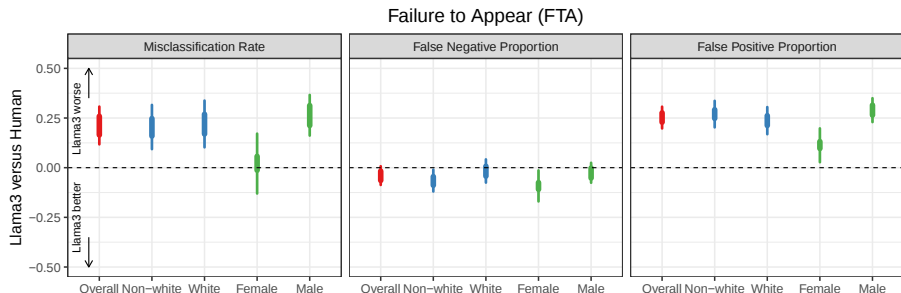
- PSA is useful only in cases with extreme recommendations

PSA is not an AI. What about the Real AI?

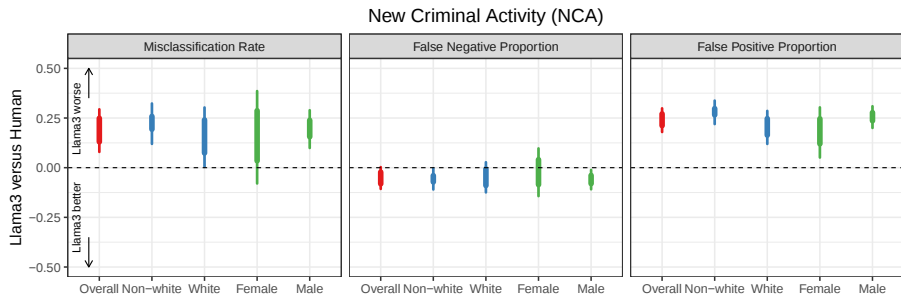
*You are a judge in Dane County, Madison, Wisconsin and are asked to decide whether or not an arrestee should be released on their own recognizance or be required to post a cash bail. If you think the risk of unnecessary incarceration is too high, then the arrestee should receive own recognizance release. On the other hand, you should assign cash bail if the following risks are too high: the risk of failure to appear at subsequent court dates, the risk of engaging in new criminal activity, and the risk of engaging in new violent criminal activity. You are provided with the following 12 characteristics about an arrestee: **[description of PSA inputs]**.*

*This arrestee has the following characteristics: **[arrestee's PSA inputs]**. Should this arrestee be released on their own recognizance or given cash bail? Please provide your answer in binary form (0 for released on their own recognizance and 1 for cash bail), followed by a detailed explanation of your decision.*

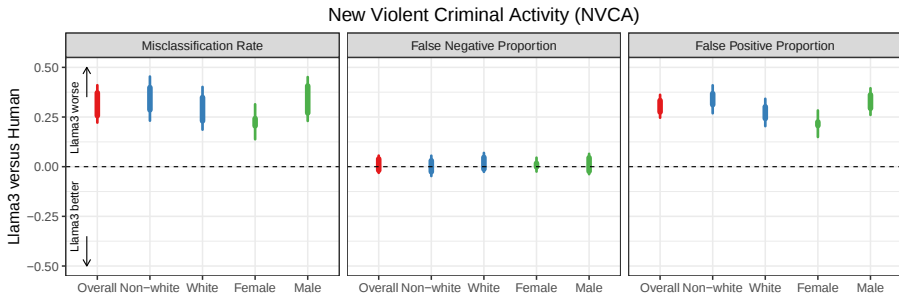
AI-alone decisions are less accurate than human decisions



AI-alone decisions are less accurate than human decisions



AI-alone decisions are less accurate than human decisions



Concluding remarks

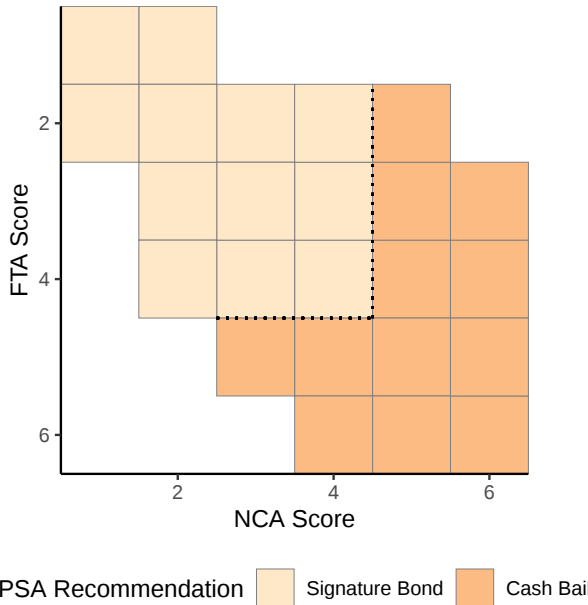
- We propose a methodological framework for evaluating three decision-making systems:
 - ① Human-alone
 - ② Human+AI
 - ③ AI-alone
- The proposed methodological framework is widely applicable
 - single-blinded treatment assignment is easy to implement
 - unconfoundedness + overlap enable RCT and observational studies
 - do not require AI-alone treatment condition
 - no additional assumption is required
 - open-source R software package **aihuman** is available
- We conducted and analyzed an RCT that evaluates the pretrial risk assessment instrument (PSA-DMF sytem):
 - ① PSA recommendations do not improve human decisions
 - ② Only extreme PSA recommendations are useful
 - ③ Both PSA and AI decisions perform worse than human decisions

PSA Scoring Rule

Risk factor		FTA	NCA	NVCA
Current violent offense	> 20 years old			2
	≤ 20 years old			3
Pending charge at time of arrest		1	3	1
Prior conviction	misdemeanor or felony	1	1	1
	misdemeanor and felony	1	2	1
Prior violent conviction	1 or 2		1	1
	3 or more		2	2
Prior sentence to incarceration			2	
Prior FTA in past 2 years	only 1	2	1	
	2 or more	4	2	
Prior FTA older than 2 years		1		
Age	22 years or younger		2	

- FTA: $\{0 \rightarrow 1, 1 \rightarrow 2, 2 \rightarrow 3, (3, 4) \rightarrow 4, (5, 6) \rightarrow 5, 7 \rightarrow 6\}$
- NCA: $\{0 \rightarrow 1, (1, 2) \rightarrow 2, (3, 4) \rightarrow 3, (5, 6) \rightarrow 4, (7, 8) \rightarrow 5, (9, 10, 11, 12, 13) \rightarrow 6\}$
- NVCA: $\{(0, 1, 2, 3) \rightarrow 0, (4, 5, 6, 7) \rightarrow 1\}$

Decision Making Framework (DMF)



PSA provision, demographics, and outcomes

	no PSA			PSA			Total (%)
	Signature bond	Cash bail <i>small</i> <i>large</i>		Signature bond	Cash bail <i>small</i> <i>large</i>		
Non-white female	64	11	6	67	6	0	154 (8)
White female	91	17	7	104	17	10	246 (13)
Non-white male	261	56	49	258	53	57	734 (39)
White male	289	48	44	276	54	46	757 (40)
FTA committed	218	42	16	221	45	16	558 (29)
<i>not</i> committed	487	90	90	484	85	97	1333 (71)
NCA committed	211	39	14	202	40	17	523 (28)
<i>not</i> committed	494	93	92	503	90	96	1368 (72)
NVCA committed	36	10	3	44	10	6	109 (6)
<i>not</i> committed	669	122	103	661	120	107	1782 (94)
Total (%)	705 (37)	132 (7)	106 (6)	705 (37)	130 (7)	113 (6)	1891 (100)