A SURVEY QUESTIONS

A.1 Fairness Judgement Questions

For all surveys, participants were asked to judge how fair it is for specific features to be used by ADMs in certain domains. Listed below are the two possible descriptions that were given for each domain, followed by the exact fairness questions asked in that domain, which were answered on a 7-point Likert scale ("Very Unfair", "Unfair", "Somewhat Unfair", "Neutral", "Somewhat Fair", "Fair", or "Very Fair"). In our first pilot survey (Section **??**), respondents were randomly assigned to receive either the first (mentions machine learning) or second (does not mention machine learning) descriptions, and then asked the 16 starred (*) questions. For all other surveys, respondents were randomly assigned one domain and asked all questions for that domain in a random order. For the full surveys as HTML files, the data files, and our code, see https://github.com/michelealbach/cross-domain-fairness.

A.1.1 Bail. **Version 1:** "When judges are deciding whether or not to grant bail to a defendant in the United States, they must consider the chance that the defendant will reoffend if set free. COMPAS (Correctional Offender Management Profiling for Alternative Sanctions) is a machine learning computer program used in some US courts to predict the risk that a defendant will reoffend. The program uses information that is obtained from a questionnaire filled out by the defendant and outputs a risk score. Judges can then use the risk score to help with bail decisions. The following questions are about how fair it would be, in your opinion, if the program used certain information to calculate the score. For each question, please choose an option from very unfair to very fair."

Version 2: "When judges are deciding whether or not to grant bail to a defendant in the United States, they must consider the chance that the defendant will reoffend if set free. In order to predict if they will reoffend, some judges use information that is obtained from a questionnaire filled out by the defendant. The following questions are about how fair it would be, in your opinion, if judges used certain information to make these decisions. For each question, please choose an option from very unfair to very fair."

- How fair is it to determine if a person can be released on bail using information about the **current charges**?
- *How fair is it to determine if a person can be released on bail using information about their **criminal history**?
- *How fair is it to determine if a person can be released on bail using information about their **substance abuse history**?
- How fair is it to determine if a person can be released on bail using information about their **stability of employment and living situation**?
- How fair is it to determine if a person can be released on bail using information about their **personality** (for example, obtained through the question "do you have the ability to "sweet talk" people into getting what you want?")?
- How fair is it to determine if a person can be released on bail using information about their **criminal attitudes** (for example, obtained through the question "do you think that a hungry person has a right to steal?")?
- *How fair is it to determine if a person can be released on bail using information about the **safety of their neighbourhood**?
- How fair is it to determine if a person can be released on bail using information about the **criminal history of their friends and family**?

- How fair is it to determine if a person can be released on bail using information about the **quality of their social life and free time** (for example, obtained through the question "do you often feel left out of things?")?
- *How fair is it to determine if a person can be released on bail using information about their **level of education**?

A.1.2 CPS. **Version 1:** "In the county of Allegheny, Pennsylvania, USA, a machine learning computer program called the Allegheny Family Screening Tool is used by the county's CPS (Child Protective Services) to help hotline staff decide whether or not a tip should be screened in, meaning to start a CPS investigation. The program uses information about the family/people involved in the tip and outputs a risk score that predicts the probability that a child will be removed from the home within 2 years if the tip is screened in. The following questions are about how fair it would be, in your opinion, if the program used certain information to calculate the score. For each question, please choose an option from very unfair to very fair."

Version 2: "In the county of Allegheny, Pennsylvania, USA, hotline staff at the county's CPS (Child Protective Services) receive tips and must decide whether or not they should be screened in, meaning to start a CPS investigation. The staff members use information about the family/people involved in the tip to predict the chance that a child would be removed from the home if the tip is screened in. The following questions are about how fair it would be, in your opinion, if the staff used certain information to make these decisions. For each question, please choose an option from very unfair to very fair."

- How fair is it to determine whether or not a tip should be screened in to CPS using information about the **demographics of the child victim** (excluding race)?
- How fair is it to determine whether or not a tip should be screened in to CPS using information about the **CPS history of the child victim**?
- How fair is it to determine whether or not a tip should be screened in to CPS using information about the **juvenile justice history of the child victim**?
- How fair is it to determine whether or not a tip should be screened in to CPS using information about the **public welfare history of the child victim**?
- How fair is it to determine whether or not a tip should be screened in to CPS using information about the **demographics of the parents or other involved adults** (excluding race)?
- How fair is it to determine whether or not a tip should be screened in to CPS using information about the **public welfare history of the parents or other involved adults**?
- How fair is it to determine whether or not a tip should be screened in to CPS using information about the **demographics of the alleged perpetrators** (excluding race)?
- How fair is it to determine whether or not a tip should be screened in to CPS using information about the **public welfare history of the alleged perpetrators**?
- How fair is it to determine whether or not a tip should be screened in to CPS using information about the **CPS history of all individuals named in the referral**?
- How fair is it to determine whether or not a tip should be screened in to CPS using information about the **behavioural health history of all individuals named in the referral**?

A.1.3 Hospital Resources. **Version 1:** "When a patient is released from the hospital, it is beneficial for doctors to be aware of the chance that the person will be readmitted in the near future so that they can provide additional care to prevent readmission. PARR-30 (Patients at Risk of Readmission within 30 days) is a machine learning computer program that uses information about the patient and outputs a risk score representing the chance that they will be readmitted within 30 days. The following questions are about how fair it would be, in your opinion, if the program used certain information to calculate the score. For each question, please choose an option from very unfair to very fair."

Version 2: "When a patient is released from the hospital, it is beneficial for doctors to be aware of the chance that the person will be readmitted in the near future so that they can provide additional care to prevent readmission. Doctors estimate the chance that a patient will be readmitted using information about the patient. The following questions are about how fair it would be, in your opinion, if the doctors used certain information to decide whether to provide additional care in order to prevent readmission. For each question, please choose an option from very unfair to very fair."

- *How fair is it to allocate additional doctor care to prevent readmission using information about a patient's **age**?
- *How fair is it to allocate additional doctor care to prevent readmission using information about a patient's **gender**?
- How fair is it to allocate additional doctor care to prevent readmission using information about a patient's **race**?
- *How fair is it to allocate additional doctor care to prevent readmission using information about a patient's **place of residence**?
- How fair is it to allocate additional doctor care to prevent readmission using information about the **hospital where they were treated**?
- How fair is it to allocate additional doctor care to prevent readmission using information about a patient's **current hospital admission**?
- How fair is it to allocate additional doctor care to prevent readmission using information about a patient's **number of emergency hospital discharges**?
- *How fair is it to allocate additional doctor care to prevent readmission using information about a patient's **history of major health conditions**?

A.1.4 Insurance. **Version 1:** "When deciding on an applicant's insurance rates, insurance companies often use machine learning computer programs to predict the levels of risk associated with each applicant. These programs use information about the applicant and their car or home to return a score which is then used to decide what rates to set. The following questions are about how fair it would be, in your opinion, if the program used certain information to calculate the score. For each question, please choose an option from very unfair to very fair, and then explain your judgement by checking each box that applies."

Version 2: "When deciding on an applicant's insurance rates, insurance companies must predict the levels of risk associated with each applicant. To do so, employees use information about the applicant and their car or home to calculate a score which is then used to decide what rates to set. The following questions are about how fair it would be, in your opinion, if the employees used certain information to calculate the score. For each question, please choose an option from very unfair to very fair, and then explain your judgement by checking each box that applies."

- How fair is it to determine an applicant's insurance rates using information about their **age**?
- How fair is it to determine an applicant's insurance rates using information about their **gender**?
- How fair is it to determine an applicant's insurance rates using information about their **marital and family status**?
- How fair is it to determine an applicant's insurance rates using information about their **employment status**?
- How fair is it to determine an applicant's insurance rates using information about their **credit history**?

- How fair is it to determine an applicant's insurance rates using information about their **level of education**?
- How fair is it to determine an applicant's insurance rates using information about their **place of residence**?
- How fair is it to determine an applicant's insurance rates using information about their **history of major health conditions**?

A.1.5 Loan. **Version 1:** "When deciding whether or not to approve a loan application, banks often use machine learning computer programs to predict the chance that the person applying will default and be unable to pay back the bank. These programs use information about the applicant and return a score which is then used to decide whether to approve a loan. The following questions are about how fair it would be, in your opinion, if the program used certain information to calculate the score. For each question, please choose an option from very unfair to very fair."

Version 2: "When deciding whether or not to approve a loan application, banks need to consider the chance that the person applying will default and be unable to pay back the bank. To do so, employees use information about the applicant to calculate a score which is then used to decide whether to approve a loan. The following questions are about how fair it would be, in your opinion, if the employees used certain information to calculate the score. For each question, please choose an option from very unfair to very fair."

- How fair is it to determine an applicant's eligibility for a loan using information about the **loan amount**?
- *How fair is it to determine an applicant's eligibility for a loan using information about their **income**?
- *How fair is it to determine an applicant's eligibility for a loan using information about their **age**?
- How fair is it to determine an applicant's eligibility for a loan using information about their **gender**?
- *How fair is it to determine an applicant's eligibility for a loan using information about their **marital and family status**?
- How fair is it to determine an applicant's eligibility for a loan using information about their **number of dependents**?
- How fair is it to determine an applicant's eligibility for a loan using information about their **level of education**?
- How fair is it to determine an applicant's eligibility for a loan using information about their **employment status**?
- *How fair is it to determine an applicant's eligibility for a loan using information about their **credit history**?
- How fair is it to determine an applicant's eligibility for a loan using information about their **owned property value**?

A.1.6 Unemployment. **Version 1:** "In 2014, the Polish government introduced a machine learning computer program that is used to help with decision making for unemployment benefits. When an unemployed person asks for aid, the program uses information about them obtained from a questionnaire and outputs a score for their employment potential. Their score is used to determine which financial aid benefits they are eligible for. The following questions are about how fair it would be, in your opinion, if the program used certain information to calculate the score. For each question, please choose an option from very unfair to very fair."

Version 2: "In 2014, the Polish government introduced a system that is used to help with decision making for unemployment benefits. When an unemployed person asks for aid, an employee asks them a series of questions and uses the answers to calculate a score for their employment potential. Their score is used to determine which financial aid benefits they are eligible for. The following questions are about how fair it would be, in your opinion, if employees used certain information to calculate the score. For each question, please choose an option from very unfair to very fair."

- *How fair is it to determine a person's eligibility for unemployment aid using their **age**?
- *How fair is it to determine a person's eligibility for unemployment aid using their **gender**?
- *How fair is it to determine a person's eligibility for unemployment aid using their **level of education**?
- How fair is it to determine a person's eligibility for unemployment aid using their **work history over the last 5 years**?
- How fair is it to determine a person's eligibility for unemployment aid using their **professional skills**?
- *How fair is it to determine a person's eligibility for unemployment aid using their **degree of disability**?
- How fair is it to determine a person's eligibility for unemployment aid using their **time spent unemployed**?
- How fair is it to determine a person's eligibility for unemployment aid using their **place of residence**?
- How fair is it to determine a person's eligibility for unemployment aid using their **reason for wanting a job** (other than income)?
- How fair is it to determine a person's eligibility for unemployment aid using their **initiative** (for example, obtained through the question "what are you able to do to increase your chances of finding a job?")?

A.2 Necessity and Sufficiency Explanatory Questions

In our second pilot study (Section **??**), participants were asked to explain their fairness judgements after every question by checking any number of the properties or by filling in a blank text box. Depending on if they had selected a "Fair" (or "Neutral") option or an "Unfair" option, participants saw one of the following question versions after every feature fairness judgement question. [Feature] is replaced with the bolded part of the previous question.

Version 1 (Answered "Fair" or "Neutral"): "Please explain why you think it is fair / neither fair nor unfair to use information about their [feature]. You may do so by checking any number of the following suggestions or by filling in the blank option at the bottom."

- Their [feature] can be assessed reliably
- Their [feature] is relevant to [outcome] decisions
- Their [feature] is not private
- Their [feature] is caused by choices made by the person
- Their [feature] can cause them to have a high risk level
- Making this decision using information about their [feature] cannot cause a vicious cycle
- Making this decision using information about their [feature] cannot have negative effects on certain groups of people that are protected by law (eg., based on race, gender, age, religion, national origin, disability status)
- Their [feature] cannot be caused by their belonging to a group protected by law (eg., based on race, gender, age, religion, national origin, disability status)
- Other: (fill in the blank)

Version 2 (Answered "Unfair"): "Please explain why you think it is unfair to use information about their [feature]. You may do so by checking any number of the following suggestions or by filling in the blank option at the bottom."

- Their [feature] cannot be assessed reliably
- Their [feature] is not relevant to [outcome] decisions
- Their [feature] is private
- Their [feature] is not caused by choices made by the person
- Their [feature] cannot cause them to have a high risk level
- Making this decision using information about their [feature] can cause a vicious cycle
- Making this decision using information about their [feature] can have negative effects on certain groups of people that are protected by law (eg., based on race, gender, age, religion, national origin, disability status)
- Their [feature] can be caused by their belonging to a group protected by law (eg., based on race, gender, age, religion, national origin, disability status)
- Other: (fill in the blank)

A.3 Property Assignment Questions

In all of our non-pilot surveys, participants were asked to rate how strongly they felt the features held each of the eight properties (plus the ninth property *increases accuracy* in our later survey), randomly before or after making their fairness judgements. Listed below are the property assigning statements that participants were asked to rate how much they agreed with on a 7-point Likert scale ("Strongly Disagree", "Disagree", "Somewhat Disagree", "Neutral", "Somewhat Agree", "Agree", or "Strongly Agree") for each feature.

- Information about their [feature] can be assessed **reliably**.
- Information about their [feature] is **relevant** to [outcome] decisions. / Using information about their [feature] would increase the **accuracy** of [outcome] decisions.
- Information about their [feature] is **private**.
- A person can change their [feature] by making a **choice or decision**.
- Their [feature] can **cause** them to [have an outcome].
- Making this decision using information about their [feature] can cause a **vicious cycle**.
- Making this decision using information about their [feature] can have **negative effects on certain groups** of people that are protected by law (e.g., based on race, gender, age, religion, national origin, disability status).
- Their [feature] can be **caused by their belonging to a group** protected by law (e.g., race, gender, age, religion, national origin, disability status).

A.4 Demographic Questions

With the exception of the first pilot survey, all participants were asked the following (optional) demographic questions.

(1) Select the box that corresponds to your age:
    - 18-29
    - 30-39
    - 40-49
    - 50-59
    - 60-69
    - 70 or above
(2) Select the box that describes your current completed level of education:

- Less than high school degree
- High school degree or equivalent
- Associate degree or diploma
- Bachelor degree
- Graduate degree

(3) Select the box that best describes how you identify:
- Female
- Male
- Nonbinary
- Other: (fill in the blank)

(4) Select the box that best describes your annual household income in American dollars:
- Less than $25,000
- $25,000 to $50,000
- $50,000 to $75,000
- $75,000 to $100,000
- Over $100,000

(5) Select all boxes that apply to you:
- Aboriginal/Indigenous
- Asian
- Black/African
- Caucasian
- Hispanic/Latinx
- Other: (fill in the blank)

B SUPPLEMENTARY TABLES AND FIGURES

Table 1 lists the consensus levels achieved in our initial survey as described in Section **??**. For each feature in each domain, we provide the consensus (as measured by 1 minus the normalized Shannon entropy) that the feature exhibits each property; the mean consensus over properties for that feature; and the consensus about the fairness of the feature. The last two columns are correlated with a very strong Pearson correlation coefficient of 0.72.

Table 2 shows the hypothetical sample sizes that would result in American census-representative [1] sampler demographic groups per domain. In other words, because of our large total sample size, we would have equal total numbers of respondents from each demographic group as a American census-representative sample of the given size. Values listed as $< n$ are larger than our actual sample size per domain meaning that we over-sampled that demographic group.

Tables 3 and 4, as well as Figures 1, 2, 3, and 4 are identical to Table **??** and Figures **??** and **??** but using data without any Caucasians or males.

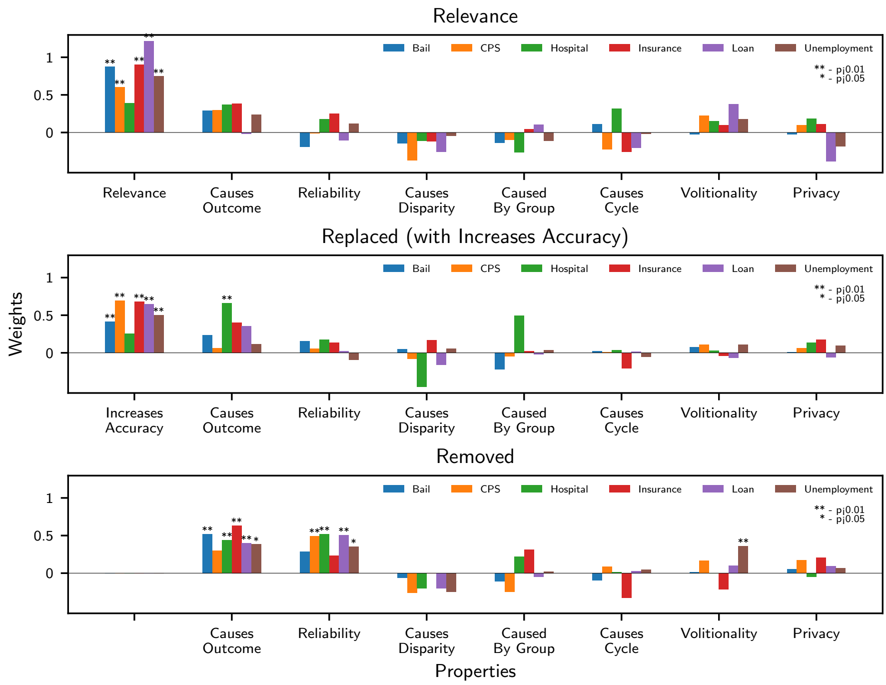

Fig. 1. Identical to Figure ??, but using data without Caucasians. Figure ?? caption: The weights associated with each property in every domain for the full property models of the initial survey (Relevance), the survey that replaced *relevance* with *increases accuracy* (Replaced), and the survey that removed *relevance* all together (Removed). Significant weights (using a linear regression t-test with the null hypothesis that the coefficient values are equal to zero) at the $p < 0.05$ (*) and $p < 0.01$ (**) levels are indicated.

Table 3. Identical to Table ??, but using data without Caucasians. Table ?? caption: The average accuracies and standard errors of the mean for the within-domain, all-domain, and cross-domain predictors (predicting fairness judgements using property assignments). *Within:* Accuracies obtained by training and testing the model within the listed domain (or over all pooled domains), each average is over 1000 50%/50% train/test splits. *Cross Trained:* Accuracies obtained by training in the listed domain and testing in each of the other domains individually, average is over the five other domains used to test. *Cross Tested:* Accuracies obtained by training in each of the other domains individually and testing in the listed domain, average is over the five other domains used to train.

Domain	Within	Cross Trained	Cross Tested
Bail	79.2 ± 0.00098%	79.0 ± 0.018%	77.0 ± 0.018%
CPS	83.0 ± 0.00075%	73.2 ± 0.037%	78.1 ± 0.011%
Hospital	77.0 ± 0.00128%	76.8 ± 0.014%	75.5 ± 0.016%
Insurance	78.0 ± 0.00099%	78.0 ± 0.014%	74.8 ± 0.040%
Loan	83.3 ± 0.00101%	77.0 ± 0.018%	82.2 ± 0.011%
Unemployment	77.7 ± 0.00091%	80.8 ± 0.011%	77.2 ± 0.009%
All (Pooled)	80.7 ± 0.00037%	N/A	N/A

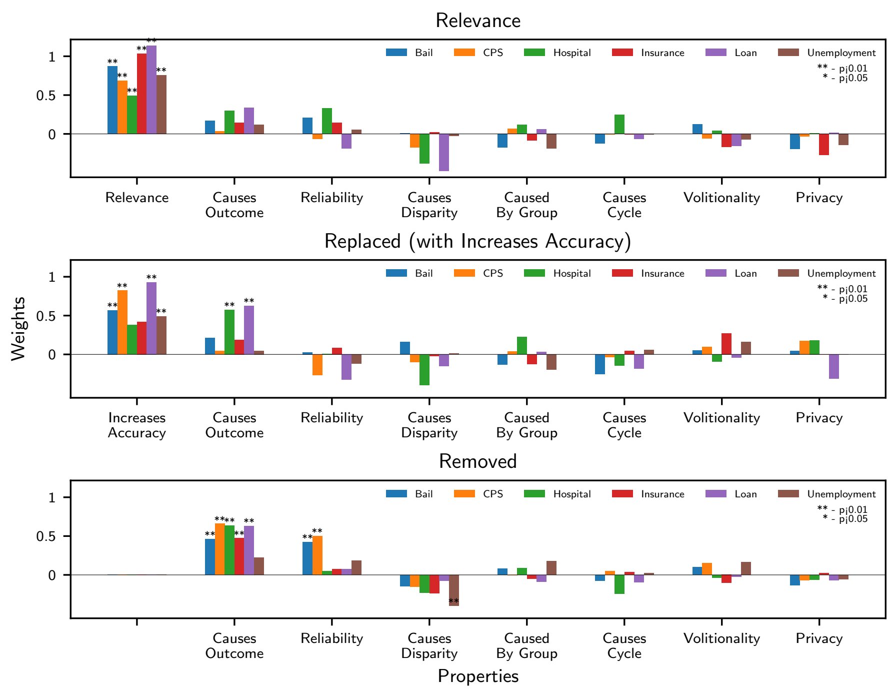

Fig. 2. Identical to Figure ??, but using data without males. Figure ?? caption: The weights associated with each property in every domain for the full property models of the initial survey (Relevance), the survey that replaced *relevance* with *increases accuracy* (Replaced), and the survey that removed *relevance* all together (Removed). Significant weights (using a linear regression t-test with the null hypothesis that the coefficient values are equal to zero) at the $p < 0.05$ (*) and $p < 0.01$ (**) levels are indicated.

Table 4. Identical to Table ??, but using data without males. Table ?? caption: The average accuracies and standard errors of the mean for the within-domain, all-domain, and cross-domain predictors (predicting fairness judgements using property assignments). *Within:* Accuracies obtained by training and testing the model within the listed domain (or over all pooled domains), each average is over 1000 50%/50% train/test splits. *Cross Trained:* Accuracies obtained by training in the listed domain and testing in each of the other domains individually, average is over the five other domains used to test. *Cross Tested:* Accuracies obtained by training in each of the other domains individually and testing in the listed domain, average is over the five other domains used to train.

Domain	Within	Cross Trained	Cross Tested
Bail	81.8 ± 0.00027%	80.3 ± 0.013%	82.6 ± 0.004%
CPS	79.9 ± 0.00075%	79.6 ± 0.023%	78.1 ± 0.015%
Hospital	76.7 ± 0.00085%	80.7 ± 0.008%	75.3 ± 0.010%
Insurance	80.2 ± 0.00088%	78.3 ± 0.027%	78.7 ± 0.013%
Loan	87.0 ± 0.00058%	79.3 ± 0.010%	85.3 ± 0.007%
Unemployment	78.8 ± 0.00069%	81.1 ± 0.019%	79.3 ± 0.004%
All (Pooled)	81.4 ± 0.00027%	N/A	N/A

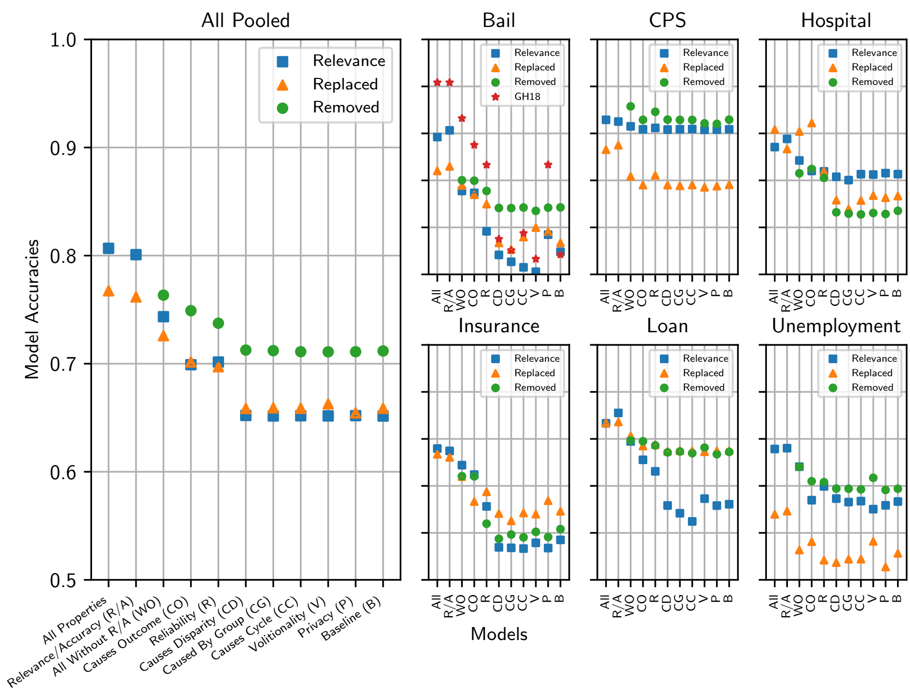

Fig. 3. Identical to Figure ??, but using data without Caucasians. Figure ?? caption: The accuracy levels achieved per model. For each domain (and all pooled), the accuracies achieved from the initial survey (Relevance) and additional surveys (Replaced and Removed) are shown for the following models where applicable: using all eight properties, using only *relevance/increases accuracy*, using all seven properties excluding *relevance/increases accuracy*, and each of the other seven properties individually. Additionally for comparison, we show the baseline accuracies that are achived by guessing only either “fair” or “unfair” (whichever does better). Error bars are present for each point but are too small to be visible.

REFERENCES

[1] U.S. Census Bureau. 2018. 2014—2018 ACS 5-Year Data Profile. (2018). https://www.census.gov/acs/www/data/data-tables-and-tools/data-profiles/2018/

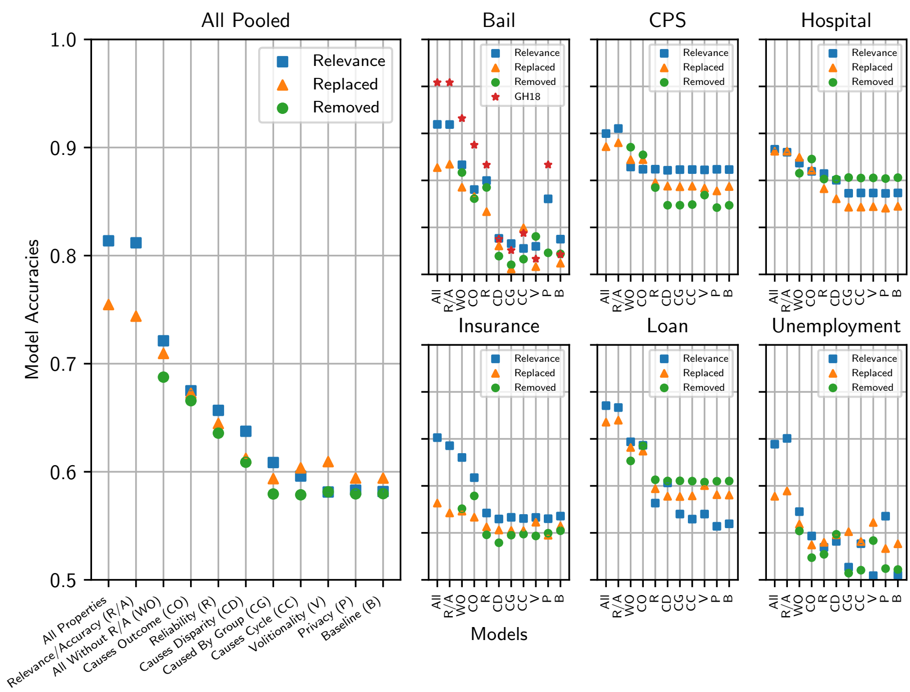

Fig. 4. Identical to Figure ??, but using data without males. Figure ?? caption: The accuracy levels achieved per model. For each domain (and all pooled), the accuracies achieved from the initial survey (Relevance) and additional surveys (Replaced and Removed) are shown for the following models where applicable: using all eight properties, using only *relevance/increases accuracy*, using all seven properties excluding *relevance/increases accuracy*, and each of the other seven properties individually. Additionally for comparison, we show the baseline accuracies that are achived by guessing only either "fair" or "unfair" (whichever does better). Error bars are present for each point but are too small to be visible.

Table 1. Consensus levels achieved in our initial survey as described in Section ??. The values are 1 minus the Shannon entropy normalized between 0 and 1 (over responses bucketed into the categories "Unfair", "Neutral", and "Fair") so that 1 corresponds to complete consensus and 0 to complete disagreement. The eight columns corresponding to our eight properties are the levels of consensus reached when assigning that property to each feature, and the property average column is the average of the eight previous columns. The fairness column lists the levels of consensus achieved when rating how fair that feature is. The last two columns are correlated with a very strong Pearson correlation coefficient of 0.72

Domain	Feature	Relev.	C.O.	Reliab.	C.D.	C.G	C.C.	Vol.	Priv.	Prop. Avg.	Fairness
Bail	Current Charges	0.792	0.336	0.853	0.066	0.134	0.071	0.186	0.286	0.341	0.792
Bail	Criminal History	0.937	0.339	0.893	0.084	0.134	0.116	0.240	0.303	0.381	0.746
Bail	Substance Abuse	0.638	0.465	0.385	0.024	0.055	0.288	0.164	0.088	0.263	0.372
Bail	Employment & Living	0.379	0.238	0.427	0.121	0.067	0.171	0.379	0.238	0.253	0.231
Bail	Personality	0.153	0.313	0.254	0.084	0.098	0.048	0.124	0.037	0.139	0.106
Bail	Criminal Attitudes	0.175	0.159	0.153	0.010	0.006	0.056	0.308	0.059	0.116	0.132
Bail	Neighbourhood	0.195	0.036	0.374	0.198	0.091	0.086	0.201	0.250	0.179	0.217
Bail	Friends and Family	0.148	0.135	0.229	0.217	0.088	0.131	0.272	0.113	0.167	0.432
Bail	Social Life	0.124	0.126	0.241	0.043	0.031	0.063	0.349	0.185	0.145	0.329
Bail	Education	0.295	0.195	0.478	0.134	0.046	0.108	0.152	0.109	0.190	0.290
CPS	Child Demographics	0.149	0.093	0.292	0.145	0.200	0.147	0.156	0.039	0.153	0.198
CPS	Child CPS His.	0.615	0.393	0.549	0.102	0.074	0.027	0.113	0.144	0.252	0.749
CPS	Juvenile Justice His.	0.546	0.333	0.710	0.130	0.079	0.138	0.121	0.087	0.268	0.420
CPS	Child Welfare His.	0.457	0.159	0.378	0.041	0.063	0.076	0.154	0.116	0.180	0.355
CPS	Parent Demographics	0.205	0.057	0.394	0.295	0.210	0.114	0.209	0.067	0.194	0.174
CPS	Parent Welfare His.	0.232	0.161	0.395	0.164	0.091	0.080	0.106	0.102	0.167	0.365
CPS	Perp Demographics	0.218	0.043	0.311	0.279	0.161	0.181	0.095	0.066	0.169	0.138
CPS	Perp Welfare His.	0.285	0.221	0.443	0.092	0.090	0.006	0.121	0.072	0.166	0.320
CPS	All CPS His.	0.521	0.369	0.446	0.105	0.122	0.082	0.196	0.095	0.242	0.494
CPS	All Health His.	0.653	0.379	0.317	0.168	0.049	0.132	0.079	0.113	0.236	0.528
Hospital	Age	0.647	0.220	0.679	0.094	0.098	0.080	0.432	0.133	0.298	0.297
Hospital	Gender	0.338	0.088	0.584	0.122	0.029	0.116	0.057	0.098	0.179	0.107
Hospital	Race	0.096	0.115	0.264	0.205	0.088	0.036	0.528	0.120	0.181	0.226
Hospital	Place of Residence	0.110	0.087	0.324	0.117	0.048	0.049	0.490	0.222	0.181	0.090
Hospital	Hospital Treated	0.400	0.100	0.796	0.155	0.181	0.109	0.107	0.124	0.246	0.143
Hospital	Admission	0.714	0.091	0.856	0.175	0.171	0.106	0.109	0.248	0.309	0.487
Hospital	No. of Discharges	0.751	0.092	0.761	0.194	0.167	0.041	0.117	0.209	0.292	0.378
Hospital	History of Health	0.834	0.578	0.613	0.157	0.072	0.079	0.236	0.323	0.362	0.761
Insurance	Age	0.573	0.580	0.697	0.311	0.028	0.010	0.554	0.088	0.355	0.294
Insurance	Gender	0.117	0.080	0.419	0.292	0.119	0.022	0.141	0.023	0.152	0.355
Insurance	Marital and Family	0.060	0.096	0.256	0.021	0.020	0.053	0.326	0.037	0.109	0.195
Insurance	Employment	0.157	0.169	0.354	0.095	0.050	0.019	0.238	0.071	0.144	0.153
Insurance	Credit	0.231	0.128	0.378	0.070	0.032	0.224	0.141	0.099	0.163	0.198
Insurance	Education	0.122	0.058	0.256	0.144	0.020	0.021	0.255	0.015	0.111	0.265
Insurance	Place of Residence	0.095	0.095	0.378	0.145	0.092	0.022	0.341	0.068	0.155	0.164
Insurance	History of Health	0.359	0.493	0.124	0.229	0.161	0.200	0.113	0.420	0.262	0.202
Loan	Loan Amount	0.857	0.507	0.836	0.178	0.200	0.044	0.456	0.058	0.392	0.722
Loan	Income	0.858	0.717	0.573	0.065	0.107	0.024	0.271	0.078	0.337	0.896
Loan	Age	0.202	0.112	0.591	0.204	0.081	0.048	0.470	0.109	0.227	0.199
Loan	Gender	0.475	0.498	0.268	0.340	0.128	0.062	0.105	0.071	0.243	0.573
Loan	Marital and Family	0.133	0.019	0.390	0.061	0.033	0.020	0.351	0.024	0.129	0.084
Loan	No. of Dependents	0.194	0.070	0.456	0.054	0.044	0.010	0.074	0.037	0.118	0.094
Loan	Education	0.125	0.171	0.273	0.096	0.035	0.039	0.253	0.090	0.135	0.134
Loan	Employment	0.754	0.531	0.620	0.132	0.108	0.031	0.426	0.214	0.352	0.754
Loan	Credit	0.834	0.095	0.681	0.120	0.128	0.039	0.271	0.184	0.294	0.734
Loan	Property	0.679	0.074	0.433	0.055	0.077	0.017	0.190	0.127	0.207	0.392
Unem.	Age	0.177	0.314	0.520	0.354	0.171	0.208	0.324	0.081	0.269	0.196
Unem.	Gender	0.287	0.217	0.232	0.295	0.275	0.114	0.100	0.018	0.192	0.379
Unem.	Education	0.283	0.389	0.476	0.200	0.101	0.172	0.268	0.126	0.252	0.270
Unem.	Work History	0.570	0.379	0.659	0.141	0.124	0.120	0.191	0.155	0.292	0.440
Unem.	Skills	0.432	0.162	0.540	0.094	0.156	0.066	0.187	0.155	0.224	0.318
Unem.	Disability	0.335	0.495	0.256	0.350	0.167	0.193	0.258	0.153	0.276	0.164
Unem.	Time Unemployed	0.268	0.313	0.400	0.105	0.096	0.214	0.046	0.063	0.188	0.172
Unem.	Place of Residence	0.203	0.061	0.305	0.123	0.121	0.170	0.284	0.061	0.166	0.313
Unem.	Reason	0.125	0.021	0.180	0.125	0.065	0.028	0.383	0.032	0.120	0.039
Unem.	Initiative	0.263	0.304	0.141	0.212	0.073	0.053	0.433	0.015	0.187	0.126

Table 2. The hypothetical sample sizes for which our total number of respondents in each demographic group would be exactly representative of the United States population [1] rounded to the nearest whole number. Values expressed as >n are larger than the sample size that we actually had for that domain, indicating that we over-sampled that demographic group. For most of the demographic groups that we under-sampled, we still have more total respondents than an American representative sample of 100 people would have.

Demographic Group	Bail	Unem.	CPS	Hos.	Loan	Ins.
18-29	>279	>282	>279	>277	>278	>274
30-39	>279	>282	>279	>277	>278	>274
40-49	>279	>282	>279	>277	>278	>274
50-59	195	203	219	227	195	219
60-69	114	170	91	68	68	136
70 up	63	109	47	47	16	16
Less than HS	0	8	0	16	8	24
High School	126	132	113	138	113	105
Associate or Diploma	>279	>282	>279	>277	>278	>274
Bachelor Degree	>279	>282	>279	>277	>278	>274
Graduate Degree	>279	>282	>279	240	>278	>274
Female	220	253	211	216	209	197
Male	>279	>282	>279	>277	>278	>274
<$25000	218	257	277	>277	238	208
$25000-$50000	>279	>282	>279	>277	>278	>274
$50000-$75000	>279	>282	>279	>277	>278	>274
$75000-$100000	248	240	>279	256	>278	>274
>$100000	100	82	82	72	100	111
Aboriginal	59	235	235	235	235	>274
Asian	>279	>282	>279	>277	>278	>274
Black	214	243	136	143	157	186
Caucasian	245	260	216	262	224	260
Hispanic	67	124	101	79	107	101