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

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We examine justice in data-aided decisions in the context of a scarce societal resource allocation problem. Non-experts (recruited on Amazon Mechanical Turk) have to determine which homeless households to serve with limited housing assistance. We empirically elicit decision-maker preferences for whether to prioritize more vulnerable households or households who would best take advantage of more intensive interventions. We present three main findings. (1) When vulnerability or outcomes are quantitatively conceptualized and presented, humans (at a single point in time) are remarkably consistent in making either vulnerability- or outcome-oriented decisions. (2) Prior exposure to quantitative outcome predictions has a significant effect and changes the preferences of human decision-makers from vulnerability-oriented to outcome-oriented about one-third of the time. (3) Presenting algorithmically-derived risk predictions in addition to household descriptions reinforces decision-maker preferences. Among the vulnerability-oriented, presenting the risk predictions leads to a significant increase in allocations to the more vulnerable household, whereas among the outcome-oriented it leads to a significant decrease in allocations to the more vulnerable household. These findings emphasize the importance of explicitly aligning data-driven decision aids with system-wide allocation goals.

CCS Concepts: • **Applied computing** → **Psychology**; **Economics**.

Additional Key Words and Phrases: Justice, Fairness, Scarcity, Decision-making, Homelessness

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1 INTRODUCTION

Who should be prioritized for receipt of a scarce resource that is centrally controlled, funded, and allocated, in the absence of a market? This question arises in many contexts, ranging from organ donation [18], social service allocation [4], and military service [15], to entries to the New York City marathon. How institutions make these decisions has been studied under the moniker "local justice" in political philosophy, and it has become clear that different types of institutions use a range of different prioritization schemes, ranging from lotteries (military drafts) to prioritizing the most vulnerable (liver transplantation) to prioritizing those predicted to benefit most from receipt of the resource (medical triage) [13, 15]. The advent of algorithmic decision making has brought with it the ability to make such prioritization decisions in a more automated manner, often through providing decision support to humans in the form of additional information about those

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seeking the scarce resource. While there has been considerable attention paid to the possible bias of such algorithmic predictions, a key question that has not been studied thus far is how such predictions interact with decision-maker conceptualizations of justice, and the possible impacts of such interactions on the overall goals of the institution allocating the resources.

We study this issue using human subject experiments in the context of providing scarce homelessness resources. The scarce resource is one unit of *transitional housing*, an intensive and costly service that provides stable housing, along with other forms of support, for an extended period. The baseline is *emergency shelter*, a less intensive and costly service that provides space to stay for a more limited time. In the main task, participants are presented with information and asked which of two households they would prioritize for transitional housing. We are interested in choices about whether to prioritize the *more vulnerable* household for transitional housing, or the household that would have a *better outcome* from receiving transitional housing. We conceptualize baseline vulnerability as the probability of returning to homelessness within the next two years if only given emergency shelter.

We have three major hypotheses.

- H1: Decisions on scarce resource allocation primarily fall into two types – *outcome-oriented* and *vulnerability-oriented* prioritization – reflecting two common perceptions of justice. In our experiment, we will observe this as one group of decision-makers allocating transitional housing to households most likely to benefit from the service as characterized by lower probabilities of return to homelessness when receiving transitional housing (outcome-oriented prioritization), while another group prioritizes transitional housing for households with greater perceived need, as characterized by higher probabilities of return to homelessness when receiving only emergency shelter (vulnerability-oriented prioritization).
- H2: Prior exposure to outcome predictions in any form introduces a goal-framing effect, leading to decision-makers becoming more likely to be outcome-oriented in future allocation decisions.
- H3: In the absence of defined scarce resource allocation goals, the presentation of algorithmic predictions of outcomes reveals the prioritization types of decision-makers. Among outcome-oriented decision-makers, the group that sees algorithmic predictions of outcomes in addition to household information will make more allocations to transitional housing of those with better predicted outcomes from such allocations. Conversely, among vulnerability-oriented decision-makers, the group that sees algorithmic predictions of outcomes in addition to household information will make more allocations to transitional housing of those with worse predicted outcomes from emergency shelter.

We design a carefully sequenced survey instrument that we use to test the above hypotheses. Subjects, recruited on Amazon Mechanical Turk, first try to predict probabilities of return to homelessness (low, medium, or high) based on vignettes of household data (e.g. number of household members, monthly income, disabling condition) and which resource is provided (transitional housing or emergency shelter). In this task, half of the subjects receive "training" in the form of vignettes labeled with the "correct" probabilities (as predicted by a machine learning model with access to many datapoints), while the other half see the same vignettes, but without labels. The second and third tasks both ask decision-makers which of two households they would prioritize for a single spot in transitional housing, under the assumption that the other one would go into emergency shelter. The second task compares prioritizations with or without access to algorithmic predictions of vulnerability. The third task elicits decision-maker preferences when provided *only vulnerability predictions* (no household information).

We use the third task to determine decision-maker type, and find strong support for H1. Almost all the participants can be cleanly categorized as either vulnerability- or decision- oriented. The sequencing also means that this type revelation cannot affect their previous tasks, in particular Task 2. By examining whether participants had any exposure to predictions of outcomes in either Task 1 (via training) or Task 2 (via receiving predictions in addition to vignettes), we can see if such exposure influences the revealed types. We find that, among those with prior exposure, almost 2/3 reveal themselves as outcome-oriented in Task 3, while among those without prior exposure, only 1/3 reveal themselves as outcome-oriented, supporting H2. Finally, by examining the difference in behavior for those who did or did not receive predictions in addition to vignettes in Type 2, we also confirm H3: vulnerability-oriented types make many more vulnerability-oriented decisions when also presented with predictions in addition to vignettes while outcome-oriented types take many more outcome-oriented decisions when also presented with predictions (note that type revelation takes place after Task 2, so it cannot influence this result).

Taken together, our results suggest the following. Decision-makers are of three main types. The first two types are committed to being vulnerability-oriented or outcome-oriented in their decision-making, while the third type are vulnerability-oriented in the absence of outcome framing, but change to outcome-oriented when presented with prior information on algorithmic predictions of outcomes. Regardless of which type participants are, providing algorithmic predictions of outcomes in addition to vignettes allows them to "reveal their type" (as of the moment of decision-making) and consistently make scarce resource allocation decisions concordant with their type.

In addition to enhancing our scientific understanding of how human notions of justice play out in scarce resource allocation, our results also have significant policy implications. Homelessness service caseworkers have discretion in their decision-making, and institutional guidelines (which often say to prioritize the most vulnerable in many contexts) often conflict with on-the-ground evaluation measures (where return to homelessness is a significant factor). While our experiments are on a lay audience rather than homelessness caseworkers, they highlight that decision support could have significant implications in practice. For example, the framing channel we uncover (H2), could lead to more outcome-oriented decision-making on the ground, while the enhanced ability of decision-makers to make decisions concordant with their type (H3) when provided algorithmic information could lead to more consistency in decision-making, although the value of that consistency is intertwined with the reliability of algorithmic predictions in the specific domain.

2 RELATED WORK

Algorithmic decision-making increasingly influences social life and public policy. Artificial intelligence and machine learning systems today leverage massive amounts of information in order to predict future events in ways that then inform choices for intervention. Recommender systems permeate formal and informal policy decisions. For example, child protective services incorporate risk scores for abuse and neglect when placing children out of the home [7]; landlords use credit and rental histories to predict evictions when accepting new tenants [1, 29, 34, 35]; judges consider the predicted probability of recidivism when making parole decisions[2, 22].

While algorithms hold promise for improving efficiencies in allocating social resources, a growing body of evidence simultaneously warns against the potential misuses of algorithmic decision-making that could perpetuate racial, social, and economic inequities. Algorithms trained on data that capture disparities inherently reproduce biased predictions [5, 6, 11, 14, 27]. For instance, a healthcare screening system under-enrolled Black patients into needed services compared with Whites by more than half [31]; the algorithm predicted need for care based on healthcare expenditure data that historically exclude Blacks given racial disparities in access to care. Moreover, healthcare access disparities are at risk of widening due to vicious cycles that emerge as data-driven screening systems incorporate biased decisions into future predictions [16]. Thus, a potential exists for automating inequities [17, 32].

Efforts to promote fair predictive models have revealed the complexities involved in data-driven decision-making. One strategy, exemplified by the Moral Machine, aims to train machines in human ethical decision-making. The crowdsourcing platform has elicited more than 40 million decision preferences by presenting humans from nearly 250 countries with a series of unavoidable crash scenarios [3]. Recording whether humans choose to swerve or stay on course provides extensive data with which one could develop decision-making strategies for fully autonomous vehicles. Similar methods attempt to elicit preferences for food donation, organ transplantation, and homeless services recommender systems [18, 25, 42]. A critique has been that the moral machine is not the right way to reason about these issues because an algorithm should not be thought of as an individual making a decision, but rather as a policy choice [21], and the implications for the societal implications of the algorithm as a policy must be considered. Some of the work in this area does indeed focus on understanding the overall policy preferences of stakeholders [25, 42], but it remains to be seen whether the systems emerging out of this area of research will succeed in achieving fairness or preserve existing undesirable societal biases.

Another strategy attempts to define and assess the fairness of algorithmic decision-making systems. Research on COMPAS (Correctional Offender Management Profiling for Alternative Sanctions) – a proprietary algorithm used by courts in sentencing that predicts defendant risk of recidivism – has demonstrated that judges assess recidivism risk inconsistently, and frequently, include prejudices that the algorithm avoids [22]; yet, impossibility results show that algorithms cannot meet all reasonable metrics of fairness at the same time [10, 23, 33]. Fairness tradeoffs emerge depending on which aspect of fairness the decision-making system is designed to optimize, and this could reflect and potentially perpetuate human biases.

Studies of COMPAS have also revealed the complexities involved in integrating human and computer decision-making. Evidence shows that non-expert humans perform as well as algorithms in assessing recidivism risk when trained with the essential information and given immediate feedback on their accuracy [14]. However, algorithms identify the most relevant information on which to base accurate decisions more efficiently than humans, especially across many features [27]. Such findings suggest the potential value of integrating algorithmic and human strengths to achieve fairness, but attempts thus far have proved challenging. On one side, training computers on the pattern of errors made by humans and algorithms fails to improve the accuracy of the integrated decisions [38]. On the other side, presenting humans with COMPAS-generated risk predictions fails to improve their accuracy. In contrast, the presence of predictions by themselves has been known to trigger a cognitive bias (anchoring) that worsens accuracy [39, 41]. Moreover, a longstanding literature exists on framing effects that shows how the presentation of information influences subsequent decisions [40]. Such results highlight the intricacies of integrating algorithmic and human decision-making and raise warnings about unintended consequences that diminish accuracy and further threaten fairness.

3 EXPERIMENTAL DESIGN

In this section we discuss our methods for algorithmic prediction and human subjects data collection. Using administrative data on homeless service delivery, we build predictive models that can be used to measure vulnerability. Using these predictions and our data on homeless households, we conduct a survey to study decision-making when resources are scarce.

3.1 Background

Federal guidelines describe homelessness as living in an unstable or impermanent housing situation. This includes living in a homeless shelter, a car or park, sleeping on a friend's or family member's couch ("doubling-up"), or being at imminent risk for eviction. Community responses to family homelessness involve assignment to services that prevent or mitigate housing insecurity. There are four homeless services commonly assigned to first-time homeless families: emergency shelter, transitional housing, rapid rehousing, and homelessness prevention.[1] Homelessness prevention provides financial assistance to families who are at imminent risk of becoming homeless. Emergency shelters and rapid rehousing are meant to provide an immediate response to homelessness. Transitional housing provides more support, typically to those with additional barriers to stability such as disabilities or health conditions. Families can call a hotline number to request homeless services. When they call, they are allocated to one of these services at the discretion of the service provider or placed on a waiting list for services.

3.2 Data

Our analysis is based on data from the Homeless Management Information System (HMIS) of St. Louis, Missouri from 2007-2014, and has previously been used by Kube et al. [24] to study algorithmic matching of homeless households to appropriate services. This system collects information on all entries and exits from the homeless system as well as demographic, health, and housing information for all households. When combined with information from the homeless hotline active at the time, the resulting dataset contains 35 features collected upon first-time entry to the system describing 13940 households from the four federally funded homeless services described above: emergency shelter, transitional housing, rapid rehousing, and homelessness prevention.

As Homelessness Prevention does not provide housing, households whose current housing situation does not provide them with adequate shelter are not considered eligible for Homelessness Prevention. For the purposes of our analysis, if a household's prior residence is a psychiatric facility, detox center, hospital, jail or prison, hotel or motel, staying with a friend or family member, foster care or group home, rental by client, or owned by client or if their prior residence was unknown but they are not considered homeless by federal definitions, they are considered eligible for Homelessness Prevention. Otherwise, they are considered ineligible for Homelessness Prevention. Of the 13940 households in the dataset, 3448 (24.73%) are considered ineligible for Homelessness Prevention. Eligible households tend to do very well in homelessness prevention, which is relatively low-cost and therefore not scarce. The allocation strategy for ineligible households is not as clear. Therefore, our current analysis focuses on allocation of prevention-ineligible households. Transitional housing and rapid rehousing both have relatively high costs and provide housing making them scarce societal resources. A major focus of the homeless system and of this analysis is determining how best to prioritize households for scarce homeless services. Since transitional housing is relatively more intensive, we focus on choices for which household to prioritize for transitional housing, with the understanding that non-prioritized households go to emergency shelter.

3.3 Algorithmic Prediction

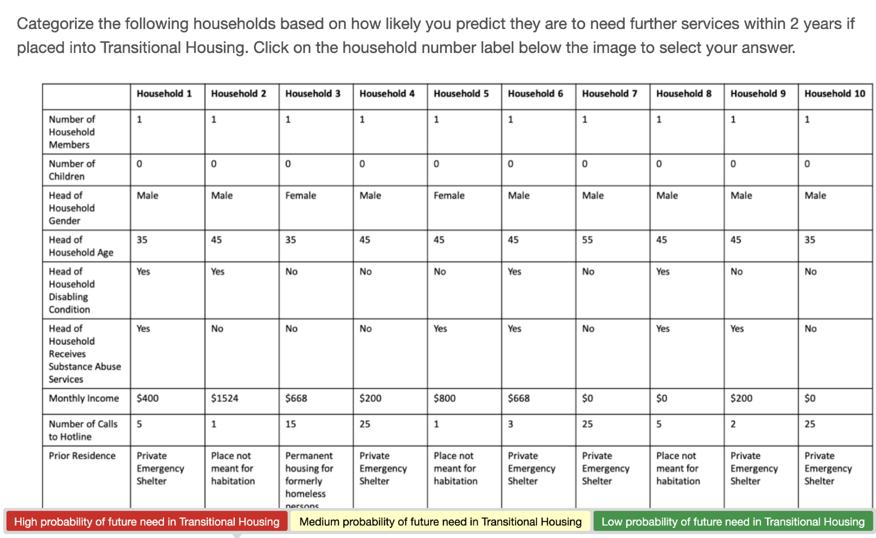
Based on the data described above, we follow Kube et al. [24] and use Bayesian Additive Regression Trees (BART) to predict the probability of households needing services within 2 years of exit from the system given placement in each service type. BART was used for its ability to capture complex patterns in data and for its usefulness in mitigating bias present in observational data for the purpose of making counterfactual predictions [9, 19]. The outcome of needing future services was constructed using information about returns to homelessness from both HMIS and the homeless hotline. This outcome, often termed 2-year reentry, is used often in homelessness research to assess

[1] A fifth service, permanent supportive housing, is targeted more towards those who may be experiencing chronic homelessness or need support for a particularly long term, and we do not consider it further here.

the utility of services. These counterfactual predictions were used in the survey described in the next section. We note that BART itself achieves an AUC value of 0.7534 on the re-entry prediction problem and is well-calibrated, and therefore it is reasonable to treat the BART prediction of reentry as a sensible measure of reentry risk.

3.4 Human Subjects Data Collection

Our experimental study consisted of three tasks, which all subjects completed in the same order.[2] We conceptualize vulnerability, as is common in the literature, as the probability of return-to-homelessness (within two years), with higher probabilities indicating higher vulnerability. Probabilities of reentry from the models described above are binned into three buckets, high, medium, and low. The first task tests the effect of training on assessing vulnerability from vignettes (the **effect-of-training** task). The second task compares prioritizations with or without access to algorithmic predictions of vulnerability (the **effect-of-algo-predictions** task). The third task elicits decision-maker preferences when provided only vulnerability predictions without other information (the **type-elicitation** task). In the first task, subjects predict which probability bucket a household falls into. The second and third tasks ask which of two households to prioritize for transitional housing, the most expensive and intense service, here treated as the scarce resource. The full survey is provided in Appendix C.



Categorize the following households based on how likely you predict they are to need further services within 2 years if placed into Transitional Housing. Click on the household number label below the image to select your answer.

	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

Fig. 1. The question posed to participants in Task 1.

*3.4.1 Task One - The **effect-of-training** Task.*

In the **effect-of-training** task, participants were randomized such that half received training in the form of ten examples of households along with the predicted probability category if that household was placed into emergency shelter or transitional housing for each household. The other half saw the same ten example vignettes without indicating probability categories. All participants were then asked to categorize 10 new households, based on vignettes, as having low, medium, or high probability of needing services again within

[2]We note that all experimental protocols were IRB-approved.

2 years given they are placed in transitional housing (see Figure 1; Figure 2 shows what the no training group sees along with an example of how probability category was indicated to the training group).

This is the same table presented previously. Models predict that the households highlighted in red have a **high** probability of needing services again within 2 years if they are given **Transitional Housing**.

	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	2	1	1
Number of Children	0	0	0	0	0	0	0	1	0	0
Head of Household Gender	Female	Male	Male	Male	Female	Female	Male	Female	Female	Female
Head of Household Age	45	35	64	55	55	23	23	23	55	45
Head of Household Disabling Condition	No	Yes	Yes	No	Yes	No	No	No	No	No
Head of Household Receives Substance Abuse Services	No	No	No	No	No	No	Yes	No	No	No
Monthly Income	$800	$668	$1524	$400	$800	$367	$0	$1068	$800	$367
Number of Calls to Hotline	15	5	2	2	2	5	0	0	2	0
Prior Residence	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Transitional Housing	Private Emergency Shelter	Private Transitional Housing	Private Transitional Housing	Private Emergency Shelter

(a) An example of what participants who receive training are shown

Here is a table of 10 examples of households needing homeless services. Each column in the table represents a different household and each row represents a piece of information that homeless service providers have when making decisions on which households should receive each kind of service. Take a few minutes to familiarize yourself with the table and try to think of the likelihood of those households needing future services if given Transitional Housing or Emergency Shelter. Then, click "I Understand" when you are ready to proceed.

	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	2	1	1
Number of Children	0	0	0	0	0	0	0	1	0	0
Head of Household Gender	Female	Male	Male	Male	Female	Female	Male	Female	Female	Female
Head of Household Age	45	35	64	55	55	23	23	23	55	45
Head of Household Disabling Condition	No	Yes	Yes	No	Yes	No	No	No	No	No
Head of Household Receives Substance Abuse Services	No	No	No	No	No	No	Yes	No	No	No
Monthly Income	$800	$668	$1524	$400	$800	$367	$0	$1068	$800	$367
Number of Calls to Hotline	15	5	2	2	2	5	0	0	2	0
Prior Residence	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Transitional Housing	Private Emergency Shelter	Private Transitional Housing	Private Transitional Housing	Private Emergency Shelter

(b) An example of what participants who do not receive training are shown

Fig. 2. A comparison of the training and no training conditions in Task 1.

3.4.2 Task Two - The ***effect-of-algo-predictions*** *Task.* In the **effect-of-algo-predictions** task, participants were presented with 10 pairs of vignettes and were asked to choose which household to prioritize for transitional housing. They were told that households who are not prioritized for transitional housing will receive emergency shelter. Half of the participants are randomized to see vignettes like those shown in Figure 3 panel (a). The other half see the same vignettes along with predictions of the probabilities that those households will need future services within 2 years if given transitional housing and if given emergency shelter as in Figure 3 panel (b). These predictions were presented as "Low", "Medium", or "High".

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	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

(a) An example question presented to the vignette only group

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	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

(b) An example question presented to the vignette and prediction group

Fig. 3. A comparison of questions from Task 2 for each randomization group

3.4.3 Task Three - The ***type-elicitation*** *Task.* In the **type-elicitation** task, participants are again presented with 10 pairs of households and asked to decide which household to prioritize for transitional housing (see Figure 4). However, this time, participants are only shown the predictions of probability of needing future services within 2 years given placement in emergency shelter and placement in transitional housing. Participants are randomized into three groups. One third of participants are not told how to make these prioritizations. This is the group we focus on in the main results. Another third are told to make *Vulnerability-Oriented* decisions. The last third are told to make *Outcome-Oriented* decisions. These last two groups are intended to check that the task makes sense and participants can make decisions that are concordant with externally specified goals. Participants then see two examples explaining how to make *Outcome-Oriented* versus *Vulnerability-Oriented* decisions. Lastly, they are told which goal to focus on and reminded of the definition of that goal before being presented with pairs of households to decide between.

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	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

Fig. 4. An example question from Task 3

3.4.4 Survey Statistics. A total of 520 participants, recruited through Amazon's Mechanical Turk platform, completed our survey. In both the **effect-of-algo-predictions** task and the **type-elicitation** task, two questions were duplicated as a reliability check. Any participant who answered inconsistently on both duplicate questions in either task was dropped from the study, resulting in 458 participants.[3] Responses were restricted to come from English speaking persons over age 18 in the United States. Of the 458 respondents, 38.81% identified as female. In a question where participants were asked to select their race, with the ability to select multiple races, 86.57% identified exclusively as white. The average age of participants was 42.34 years (SD = 12.34).

4 RESULTS

In this section, we provide evidence for our three hypotheses. First, we show there are two main "types" of decision-makers – labeled as *Vulnerability-Oriented* and *Outcome-Oriented* types – from the **type-elicitation** task. Note that we are not claiming that the type is intrinsic and unchangeable, this is the type at the time of facing the decision-making task of choosing which household to allocate the scarce resource (transitional housing) to. Second, the type of a decision maker, as determined from the **type-elicitation** task, is affected by randomization in the **effect-of-training** and **effect-of-algo-predictions** tasks such that prior exposure to predictions increases the likelihood that a decision-maker is of the *Outcome-Oriented* type. Third, the **effect-of-algo-predictions** task demonstrates that a decision-maker's type determines the effect of providing algorithmic predictions in addition to vignettes about household characteristics. *Vulnerability-Oriented* types consistently make more vulnerability-oriented decisions when provided with predictions, while *Outcome-Oriented* types consistently make more outcome-oriented decisions when provided with predictions.

[3]We repeated all analyses using the full set of participants and results remained unchanged.

4.1 H1 - Type Revelation

Recall our first hypothesis,

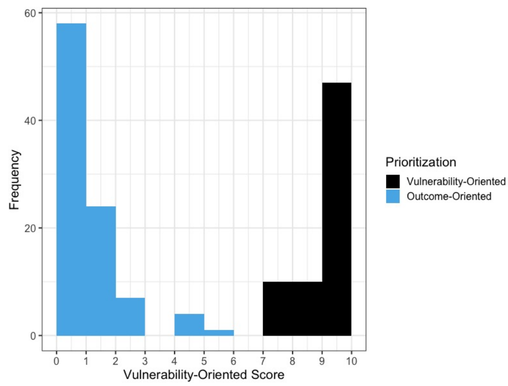
H1: Decisions on scarce resource allocation primarily fall into two types – *outcome-oriented* and *vulnerability-oriented* prioritization – reflecting two common perceptions of justice. In our experiment, we will observe this as one group of decision-makers allocating transitional housing to households most likely to benefit from the service as characterized by lower probabilities of return to homelessness when receiving transitional housing (outcome-oriented prioritization), while another group prioritizes transitional housing for households with greater perceived need, as characterized by higher probabilities of return to homelessness when receiving only emergency shelter (vulnerability-oriented prioritization).

As a reminder, in the **type-elicitation** task, we elicited prioritization goals of participants by providing them with predictions of need for future services conditional on (1) receiving transitional housing support and (2) receiving space in an emergency shelter. Given a pair of households, participants were asked to decide which of the pair should be prioritized for transitional housing, given that the other would receive space in an emergency shelter (see Figure 4). Outcomes for transitional housing were always at least as good as those for shelter. Subjects were shown predictions of likelihood those households would need future services within 2 years. These predictions were presented as "Low", "Medium", or "High." These predictions were based on a machine learning model trained on administrative data from actual households, as described in Section 3.3.

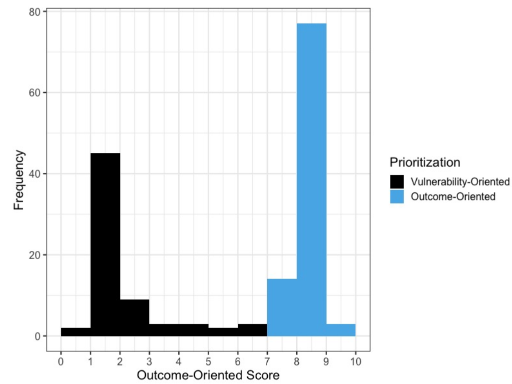
The framework of local justice [15] suggests that, given information of this kind, humans who take this information into account (as opposed to deciding randomly, for example), are likely to base their decisions on one of three possible criteria: prioritize (1) the household deemed to be most vulnerable prior to allocation; (2) the household that would be least vulnerable after allocation; or (3) the household whose vulnerability status would change the most due to the allocation. Since we use only three probability buckets to assess vulnerability to limit cognitive load, and are further limited by the constraint that transitional housing, as the scarce resource, is always at least as good as emergency shelter, it is difficult to design instances to cleanly disambiguate criterion 3 from the other two, so we focus on criteria (1) and (2).

To identify *Vulnerability-Oriented* and *Outcome-Oriented* types, we assign a score to each prioritization decision, which is a 0 if the decision is inconsistent with that prioritization type, and a 1 if it is consistent. For example, given the question posed in Figure 4, a participant who chose Household 1 made an *Outcome-Oriented* decision. As a result, we would give them an *Outcome-Oriented* score of 1 on this question. As there was no distinct *Vulnerability-Oriented* decision on this question, no *Vulnerability-Oriented* scores were assigned for this question. We sum up the scores for both criteria for each subject, and then scale the total scores to the range $[0, 10]$. We have three different randomized groups in this task – one group was told to prioritize according to the *Vulnerability-Oriented* criterion, a second group was told to prioritize according to the *Outcome-Oriented* criterion, and the third group was not given specific instructions on whom to prioritize. The first two groups serve as checks to make sure the task is properly designed (and the results are as expected – see Appendix A for details), while the third group is the one we use to assess types.

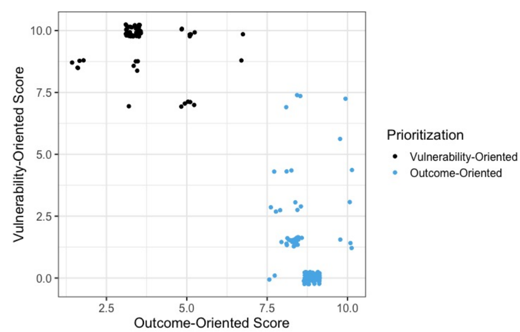
Figure 5 shows the distributions of the *Vulnerability-Oriented* and *Outcome-Oriented* scores for the group that was not asked to make a particular prioritization. We see a clear distributional difference and distinction in scores between the two types as colored by prioritization group. We define *Vulnerability-Oriented* types as those with *Vulnerability-Oriented* scores of 7 or above, and *Outcome-Oriented* types as those with *Outcome-Oriented* scores of 7 or above. Those with *Vulnerability-Oriented* scores of 7 or above are considered the *Vulnerability-Oriented* group. Of the 179 participants in the no goal group, 94 were in the the *Outcome-Oriented* group, 67 were in the



(a) Histogram of Vulnerability-Oriented Scores



(b) Histogram of Outcome-Oriented Scores



(c) Jittered Scatterplot of Outcome-Oriented Scores vs Vulnerability-Oriented Scores

Fig. 5. Histograms showing the distributions of *Vulnerability-Oriented* (a) and *Outcome-Oriented* (b) scores elicited without a prioritization goal colored by revealed prioritization type (blue for *Outcome-Oriented* and black for *Vulnerability-Oriented*) and a jittered scatterplot (c) showing the clustering of participants' by type .

Vulnerability-Oriented group, and 18 did not meet criteria for either group (both their *Outcome-Oriented* and *Vulnerability-Oriented* scores were below 7). Therefore, 90% of the participants were very consistent in their decision-making. If participants acted randomly, the probability of obtaining these results is vanishingly small. Simulating 207 participants making random decisions 100 times, the proportion assigned to a type varies between a minimum of 29.0% and a maximum of 51.7% (median 39.6%). H1 is clearly well-supported by the data.

However, as an alternative way of assigning types, *Vulnerability-Oriented* types can be defined as those whose *Vulnerability-Oriented* score is greater than their *Outcome-Oriented* score and similarly *Outcome-Oriented* types as those whose *Outcome-Oriented* score is greater than their *Vulnerability-Oriented* score. This definition results in almost the same type distribution with all 94 *Outcome-Oriented* types remaining *Outcome-Oriented* and 63 of 67 *Vulnerability-Oriented* types remaining *Vulnerability-Oriented* . Of the 18 who did not meet criteria for either type, 14 would become *Outcome-Oriented* and the remaining 4 *Vulnerability-Oriented* – Appendix B shows that our subsequent results are robust to this change in type definition.

4.2 H2 - Exposure to Predictions Makes Decision Makers Outcome-Oriented

H2: Prior exposure to outcome predictions in any form introduces a goal-framing effect, leading to decision-makers becoming more likely to be outcome-oriented in future allocation decisions.

In order to test this hypothesis, we separated respondents who were in the "no goal" condition in the **type-elicitation** task into four groups based on which randomization they received in the **effect-of-training** and **effect-of-algo-predictions** tasks. Of the four groups, only one had no prior exposure to outcome predictions (the "No Training + Vignette Only" group), whereas each of the other groups had seen outcome predictions in at least one of their prior tasks. Table 1 shows how many in each of the four groups ended up being identified as outcome-oriented versus vulnerability-oriented. The results are stark. By an almost 2:1 ratio, those with prior exposure to outcome predictions reveal themselves as outcome oriented, while those without reveal themselves as vulnerability-oriented by almost the same ratio. The results are significant at the 0.01 level as determined by a Fisher exact test (statistic value 0.0017).

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	$N = 27$	$N = 18$

Table 1. Number of participants of each prioritization type based on the **type-elicitation** task for each possible combination of randomizations in the **effect-of-training** and **effect-of-algo-predictions** tasks.

This essentially indicates that the decision making population is divided into three major sets of individuals, in almost equal proportions. Those who are vulnerability-oriented and will remain so regardless of exposure to predictions, those who are outcome oriented and will remain so regardless of exposure, and those who would be vulnerability-oriented, but switch to being outcome oriented once exposed to information about outcomes.

Analysis of potential real-world implications. These results gain importance when understanding how often *Outcome-Oriented* and *Vulnerability-Oriented* decisions diverge. In real world contexts, risk assessments provided to decision-makers are likely to be in more than the three bins (Low, Medium, High) we use here (e.g. ten, as in COMPAS, or expressed as raw probabilities). Additionally, a common situation is that there might be a large list of households calling for assistance, and only one or two spaces available. A caseworker would then have to decide which households to prioritize for those few spaces. In order to give a sense of the likelihood of divergent decisions in more realistic situations, we repeatedly sampled randomly from the original dataset of 10,043 households to find the probability of the *Vulnerability-Oriented* and *Outcome-Oriented* decisions diverging. Table 2 shows the percentage of divergent decisions when choosing between two or five households for one space in transitional housing when presenting three probability bins, ten probability bins, or raw probabilities. If we were only to compare pairs from real data using three bins, the decisions would rarely diverge, but in more realistic situations the probability of divergence grows quickly, indicating that this goal-framing effect may be of significance in real-world applications.

4.3 H3 - The Effect of Algorithmic Predictions on Decision-Making

We now turn to evidence on the differential impacts of providing algorithmic risk predictions for *Vulnerability-Oriented* and *Outcome-Oriented* types.

Presentation of Probabilities	Choosing Between Two Households	Choosing Between Five Households
3 Probability Bins	1.5%	6.0%
10 Probability Bins	13.4%	16.4%
Raw Probabilities	33.5%	63.1%

Table 2. Percentage of diverging decisions from random samples of the original dataset

H3: In the absence of defined scarce resource allocation goals, the presentation of algorithmic predictions of outcomes reveals the prioritization types of decision-makers. Among outcome-oriented decision-makers, the group that sees algorithmic predictions of outcomes in addition to household information should make more allocations to transitional housing of those with better predicted outcomes from such allocations. Conversely, among vulnerability-oriented decision-makers, the group that sees algorithmic predictions of outcomes in addition to household information should make more allocations to transitional housing of those with worse predicted outcomes from emergency shelter.

In the **effect-of-algo-predictions** task, subjects were shown ten pairs of households, and asked to prioritize one for transitional housing (see Figure 3). In each pair, one household always corresponded to the *Vulnerability-Oriented* prioritization and the other to the *Outcome-Oriented* prioritization. Subjects were randomized to see either just vignettes with information about the households, or the vignettes plus algorithmic risk prediction categories (i.e., low, medium, or high probability of re-entry conditional on receiving transitional housing or emergency shelter). We computed *Outcome-Oriented* scores for all participants (on a scale of 10 – in this task the *Vulnerability-Oriented* and *Outcome-Oriented* scores always sum to 10).

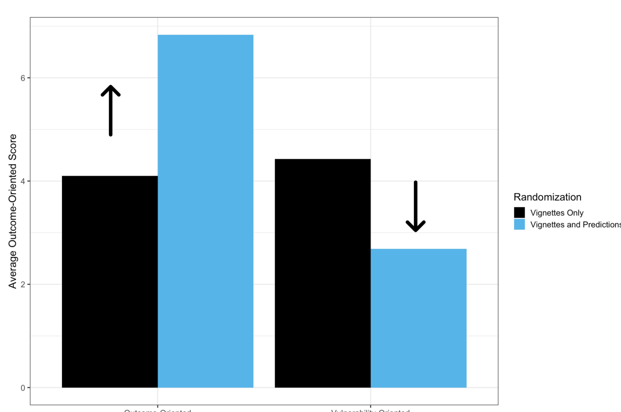


Fig. 6. Average *Outcome-Oriented* score for each prioritization type in the **effect-of-algo-predictions** task across vignette only (black) and vignette-and-risk-prediction (blue) groups. Arrows show that, when shown predictions along with vignettes, those in the *Outcome-Oriented* group have higher *Outcome-Oriented* scores and those in the *Vulnerability-Oriented* group have lower *Outcome-Oriented* scores.

Figure 6 shows that both *Vulnerability-Oriented* and *Outcome-Oriented* types have similar *Outcome-Oriented* scores (4.42(2.05) and 4.10(2.09) respectively, showing a slight lean towards prioritizing vulnerability) when shown just vignettes (no significant difference; p-value of 0.49).

However, when shown both vignettes plus risk predictions, the *Vulnerability-Oriented* types see their scores decline to 2.67(2.19), showing that they become much more aligned with making *Vulnerability-Oriented* decisions. The *Outcome-Oriented* types, on the other hand, see a dramatic *increase* in their scores, to 6.83(2.80), showing that they become much more aligned with making *Outcome-Oriented* decisions. These differences are statistically significant (p-value = 5.04e-11) and clearly substantial in their effects. This is perhaps our most salient result. Additional information, in the form of algorithmic predictions, allows individuals to consistently make decisions that are either vulnerability- or outcome- oriented, with which one being determined by that individual. This also means that the behavior of individual decision-makers should be highly predictable after seeing a few examples (when they are presented with predictions) – they will quickly reveal whether they are vulnerability- or outcome- oriented.

We note that the fact that the **type-elicitation** task is chronologically last for each subject is so that being asked to perform this task does not affect subjects' performance of the **effect-of-algo-predictions** task (in particular, the group shown just the vignette in that task). Therefore, the results related to H2 are only related to **type-elicitation** in that **type-elicitation** determines the categorization of individuals into types.

4.4 Potential Channels for the Effect in Hypothesis 3

We now turn to a discussion of the relative impacts of two potential channels, the *information* channel and the *framing* channel, for the differences in behavior when subjects see algorithmic risk predictions in addition to vignettes. If the effect were entirely or largely through the information channel, this would mean that subjects are attempting to make decisions that align with their prioritization types, but vignettes do not provide them sufficient information on vulnerability, therefore their decisions are noisier. The framing channel would instead imply that adding the information on algorithmic risk predictions makes subjects think about the implications of their choices differently, leading to different decisions.

As mentioned in Section 4.1, we have evidence that there are three main sets of individuals in the population. For simplicity, let us call them infungible outcome-oriented (IOO), infungible vulnerability-oriented (IVO), and vulnerability-to-outcome oriented (VOO). We assume that the effect we are seeing is a combination of providing the IOO and IVO individuals better information with which to make their decisions (the information effect), and of both framing and information for the VOO individuals. While disambiguating these channels is beyond the scope of the experimental design in this paper, we can shed some light on the relative information effect by considering the impact of training.

In theory, if training were perfectly successful, it would allow those who are trained to learn nothing additional from being presented predictions in addition to vignettes, and for them the information channel would be irrelevant. Then we would expect to see the training + vignette groups performing very similarly to the groups that see vignettes + predictions, which is clearly not the case.

Analyzing data from the **effect-of-training** task allows us to directly ask if subjects can be trained to make more accurate risk predictions from vignettes. In this task, subjects are shown repeated examples of vignettes paired with the algorithmic risk predictions. We then test whether they are better able to assess the risk level predicted by the algorithm. The results show a significant improvement in classification accuracy (percentage correctly classified as low, medium, or high probability of re-entry) when participants receive training (Average Classification Score for Training Group = 4.75(1.80) $N = 212$, Average Classification Score for No Training Group = 3.69(1.52) $N = 246$, p-value = 4.73e-11). However, while statistically significant, the substantive impact on prediction accuracy here is small.

In combination, our results are supportive of the hypothesis that both channels play a role in the sharp differences we see in allocation decisions between those who receive vignettes + predictions versus those who receive only vignettes. The information channel is likely dominant for IVO and IOO individuals, while both channels will affect the behavior of VOO individuals.

5 ADDITIONAL RESULTS AND IMPLICATIONS

In this section, we dig deeper into some of the results above. The results and analysis presented here are more speculative, but highlight interesting directions and connections to the existing literature.

5.1 The Interaction of Framing and Information

The cognitive bias literature suggests that presenting algorithmically derived predictions could introduce goal-framing by focusing attention on the outcomes of decisions [26, 39]. What would this suggest for the relative efficiency scores of different groups based on their types and randomization conditions? For the outcome-oriented types, we expect the ranking of efficiency scores would be:

(1) Training + Predictions would have the highest outcome-oriented scores because of repeated frames for outcomes as a goal and the presence of predictions at task time.
(2) No Training + Predictions would have the next highest outcome-oriented scores because there are no conflicting signals for making outcome-orientation a goal.
(3) Training + No Predictions would have the third highest because of a combination of framing (prior exposure through training) and the information channel (being able to make somewhat better predictions because of training).
(4) No Training + No Predictions would have the lowest efficiency among outcome-orientated decision-makers given the lack of additional outcome framing.

This is indeed the ranking we observe (Table 3), although some of the differences are small.

Expectations for the vulnerability-oriented decision-makers are less apparent. For these decision-makers, prior exposure to the outcome predictions did not change their orientation; however, the presence of algorithmically derived predictions could conflict with their vulnerability goal frame. It is interesting that Table 3 shows the lowest efficiency scores appear among vulnerability-oriented decision-makers who are presented predictions at task time; they may be reacting to the conflicting outcome frame and using the additional information from the predictions in confirming their vulnerability-orientation. The next lowest efficiency scores come from trained vulnerability-oriented decision-makers presented with predictions at task time; they may react to the framing but still attend to the additional information from predictions. The vulnerability-oriented vignette-only groups scores similarly to the outcome-oriented decision-makers from vignette-only groups.

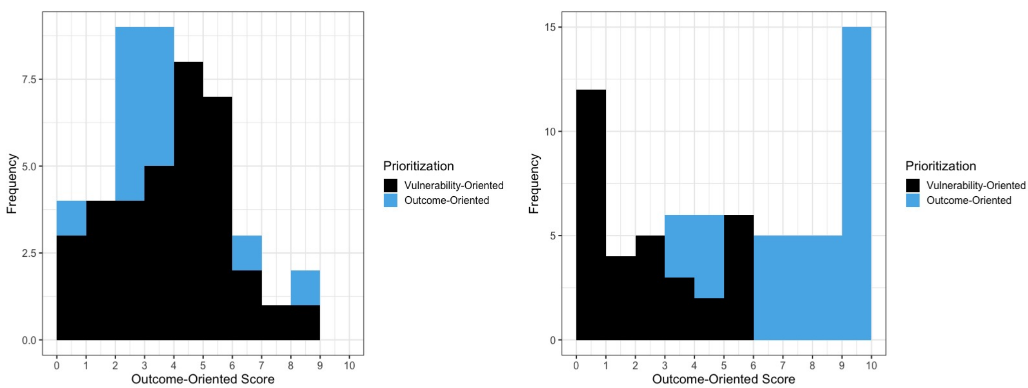
We acknowledge that the small numbers in each category necessarily make this analysis speculative, but simultaneously, suggestive of an interesting avenue for future exploration. There could also be other framing effects in play, for example one that focuses decisions on specific attributes available in the vignettes, such as the presence of children, that might interact with goal framing [26].

5.2 Consistency of Decision-Making

Figure 7 shows histograms for the outcome-oriented score for each type, separated into those who saw only the vignettes and those who saw both vignettes and predictions. If individual decision-makers are consistent, we would expect to see many scores near the extremes, with vulnerability-oriented decision-makers scoring low and outcome-oriented decision-makers scoring high. On the other hand, if individual decision-makers are inconsistent in their prioritization, that

Randomization Group	Prioritization Type	Efficiency Score M(SD)
Training + Vignette and Predictions Group	*Outcome-Oriented*	7.19(2.53), $N = 27$
No Training + Vignette and Predictions Group	*Outcome-Oriented*	6.48(3.06), $N = 27$
No Training + Vignette Only Group	*Vulnerability-Oriented*	4.70(2.01), $N = 23$
Training + Vignette Only Group	*Outcome-Oriented*	4.11(2.15), $N = 28$
No Training + Vignette Only Group	*Outcome-Oriented*	4.08(2.02), $N = 12$
Training + Vignette Only Group	*Vulnerability-Oriented*	3.92(2.11), $N = 12$
Training + Vignette and Predictions Group	*Vulnerability-Oriented*	3.07(2.13), $N = 14$
No Training + Vignette and Predictions Group	*Vulnerability-Oriented*	2.39(2.25), $N = 18$

Table 3. Means and standard deviations of efficiency scores on the **effect-of-algo-predictions** task for each possible combination of randomizations across prioritization types in descending order



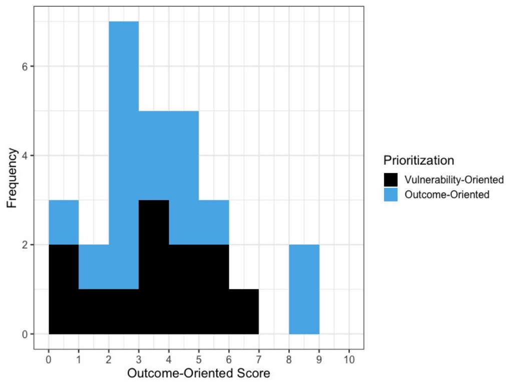
(a) Vignette Only

(b) Vignette and Prediction

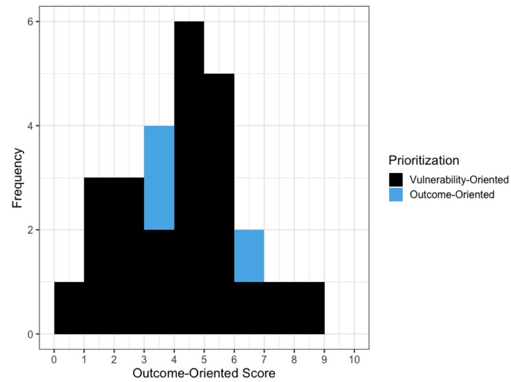
Fig. 7. Histograms showing the distribution of *Outcome-Oriented* scores on the **effect-of-algo-predictions** task for *Outcome-Oriented* types (blue) and *Vulnerability-Oriented* types (black)

would likely manifest as a unimodal distribution with modes and means close to the middle for both types. Figure 7 shows clearly that decisions are much more inconsistent when decision-makers are provided only vignettes, and are consistent when they are also provided predictions. Looking at just the means of the distributions would be confounding in this case, because the mean may not change much since each type is driven to a different extreme of the distribution.

We can also examine whether this effect is because of provision of algorithmic predictions or of framing. Figure 8 shows that there are no major differences in the histograms by type between the training and no-training groups, demonstrating quite clearly that the effect is driven by the provision of predictions at the time of decision-making. These results could have important implications in practice, since they imply an increase in procedural fairness in such scarce resource allocation tasks when additional information is provided. Inconsistency in such decisions can make them seem arbitrary to those subject to the decisions, and can often lead to a loss of trust in the system.



(a) Training Group



(b) No Training Group

Fig. 8. Histograms showing the distribution of *Outcome-Oriented* scores on the **effect-of-algo-predictions** task for those in the vignette only group separated by *Outcome-Oriented* types (blue) and *Vulnerability-Oriented* types (black)

6 DISCUSSION AND POLICY IMPLICATIONS

In her book *Automating Inequality*, Virginia Eubanks describes a common screening tool for directing homeless services that uses sensitive features in logistic regressions to predict homelessness [17]. Empirical studies have questioned the validity of the tool and potential biases against underrepresented minorities [8, 12, 37], confirming Eubanks’ concerns about automating inequities through data-driven homeless service delivery.

Federal policies, however, continue to require communities adopt an assessment for prioritizing scarce homeless services. The tool described by Eubanks remains in use along with other similar instruments that rely on sensitive features. Our study is situated in the current context faced by caseworkers [30, 36]. Demand for homeless assistance outpaces supply, and decisions about who receives services are increasingly informed by predicted probabilities – as required by policies. Our study investigates the potential implications of increasing automation in different ways, revealing some novel interactions between access to algorithmic predictions and human notions of justice in this setting.

It is important to note that we do not deem either vulnerability- or outcome-oriented prioritization as better or more useful than the other. The conditions created by conflicts between agency goals and caseworkers’ own preferences and incentives can lead to the citizenry experiencing homelessness policy very differently than intended by the political process that decides overall societal goals [28]. Current homeless policy states that prioritization for housing should be based on risk [20]. This would coincide with a vulnerability-oriented prioritization. However, homeless services are often evaluated based on efficiency; as evidenced by the literature’s focus on 2-year reentry as a metric for the usefulness of an intervention, which more closely corresponds to an outcome-oriented prioritization. This difference in priorities results in difficulties in the current system which could be exacerbated by the inclusion of an algorithmic decision-aid. Introducing additional information that can change the priorities of decision-makers should not be done without additional research. While the current study focuses on the decision-making of the general population as represented by Mechanical Turk workers, it is important to study decision-making in those training to make these decisions. The replication of this work with homeless caseworkers would help to further understand prioritization preferences as well as how, if at all, the addition of information from an algorithmic decision aid might affect homeless service allocation.

In addition, we acknowledge that those who complete surveys on Mechanical Turk might not be representative of the U.S. population as a whole. For example, our respondents were overwhelmingly white and male. There are also many possible prioritization schemes aside from the two main schemes we focus on here; though these are most closely related with the current priorities of the homeless system. Further insight into how participants are making these decisions and what criteria they weigh most heavily would help to determine additional prioritization schemes or features of families that are deemed most important in making these decisions.

Overall, our findings suggest that additional information from algorithmic decision-aids might affect more than just the efficiency or fairness of decisions made in societal contexts. The priorities and focus of human-decision makers might become more polarized and thus might fall out of line with the priorities of the social system or society as a whole. Therefore, it is important to further understand, not merely the fairness of the tools' output, or the moral reasoning of the tool, but the morals of introducing these tools and the effects they could have on our society.

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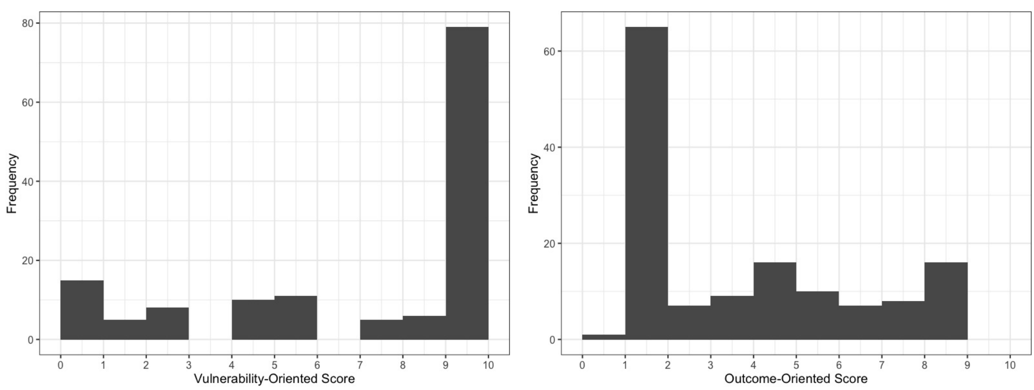
APPENDICES

A SCORE DISTRIBUTIONS FOR THE TYPE-ELICITATION TASK

Figure 9 provides histograms of *Vulnerability-Oriented* and *Outcome-Oriented* scores for participants randomized to make *Vulnerability-Oriented* decisions in the **type-elicitation** task. These scores show that most participants understood the task they were given and were able to make a high proportion of *Vulnerability-Oriented* decisions.

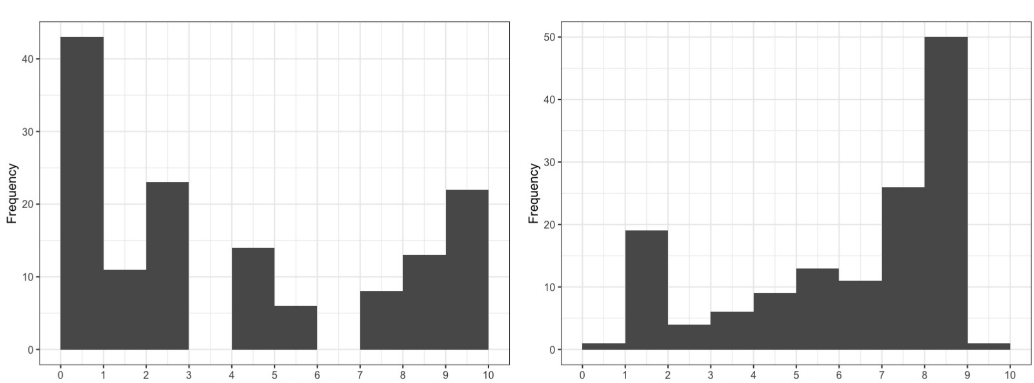
Figure 10 provides the same histograms for participants randomized to make *Outcome-Oriented* decisions in the **type-elicitation** task. Here we see participants were able to make a high proportions of *Outcome-Oriented* decisions.



(a) Histogram of *Vulnerability-Oriented* Scores

(b) Histogram of *Outcome-Oriented* Scores

Fig. 9. Histograms showing the distributions of *Vulnerability-Oriented* and *Outcome-Oriented* scores for the group told to make neediest-first decisions



(a) Histogram of *Vulnerability-Oriented* Scores

(b) Histogram of *Outcome-Oriented* Scores

Fig. 10. Histograms showing the distributions of *Vulnerability-Oriented* and *Outcome-Oriented* scores for the group told to make *Outcome-Oriented* decisions

B HYPOTHESIS 3 ROBUSTNESS CHECK

Figure 11 is an alternate version of Figure 6 where type is defined as *Vulnerability-Oriented* if the participant had a higher *Vulnerability-Oriented* score than *Outcome-Oriented* score and *Outcome-Oriented* otherwise. In this case, no participant is considered to not have a type. We see much the same main result with this type definition as the type definition described in the main paper.

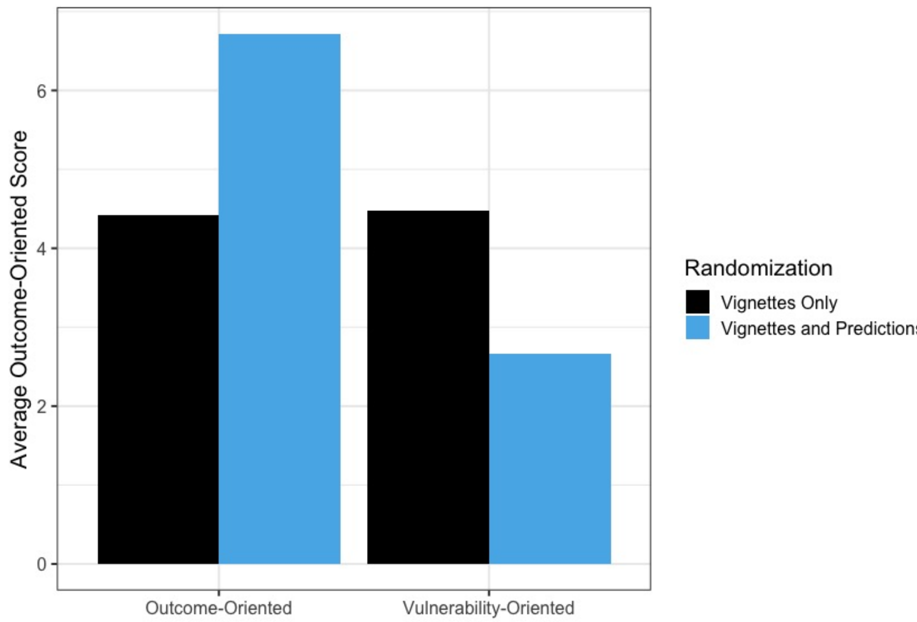


Fig. 11. Barplot comparing the average *Outcome-Oriented* score for each prioritization group across vignette only and vignette and prediction groups where types are defined by which criterion the participant scored highest on

C DATA COLLECTION INSTRUMENT

The following pages contain a copy of instructions and tasks participants saw in our online survey.

Washington University in St. Louis

Consent

Overview

Thank you for participating in research conducted by investigators from Washington University in St. Louis. The survey investigates the decision-making processes involved when allocating scarce social resources. We set the context in homeless service delivery that provide limited housing resources for households in precarious living accommodations. You will be asked to review descriptions of households seeking supports, and then, assign them to one of two potential homeless services. The survey takes about 20 minutes and is funded by the National Science Foundation award number 1939677 and Amazon.

Goal

The main goal of the survey is to better understand the ways information is used in making decisions on how to allocate scarce social resources. By providing descriptions of households seeking homeless services and asking for an assignment, we observe what decisions are made with different information. Survey data allow us to compare human decisions to those made by a computer. The study aims to improve decision-making on scarce resources for homeless service delivery. Your participation contributes to advancing our understanding.

Procedures

By continuing to the survey, you are volunteering to participate in the study. You will be introduced to the context of homeless services and the tasks involved, and then, will be asked to make a series of decisions to assign households to services. The survey is voluntary; you may stop at anytime by closing the browser. If you decide not to take part in the study or if you stop participating at any time, you won't be penalized or lose any benefits for which you otherwise qualify.

Risks and costs

We will keep the information you provide confidential. All responses will remain anonymous, and reports of study findings will not include information that identifies you.

Benefits

Although you will not gain personally, we hope that others may benefit in the future from what we learn as a result of this study. You will receive compensation for your time through the Mechanical Turk compensation platform. You will receive $3 for your participation.

Confidentiality

Again, we will keep the information you provide confidential. All responses will remain anonymous, and reports of study findings will not include information that identifies you.

Participant Certification

I have read and understand the study description. I understand the purpose of the research project and what I will be asked to do. I may stop my participation in this research study at any time and that I can refuse to answer any question(s). I hereby give my informed and free consent to be a participant in this study.

Instructions

Communities across the US provide homeless services that respond to household requests for assistance in securing stable housing. Households call a hotline to request assistance and provide basic demographic information, including household size, monthly income, whether anyone receives disability supports, and their last residence. Homeless service providers must decide what services to offer households based on the need and availability of resources.

Two key services include the following:
1) **Emergency Shelter** provides an immediate response to homelessness;
2) **Transitional Housing** provides long-term housing as well as individual case management which can include treatment for disabilities or health conditions.

Emergency Shelter consumes fewer resources to provide. Transitional Housing requires additional supports, and thus, is more scarce. Budget constraints do not allow all households to receive Transitional Housing. Those who cannot have access to Transitional Housing often receive Emergency Shelter or stay in an Emergency Shelter until space becomes available in Transitional Housing or another service.

One key outcome of interest to homeless service providers and researchers is whether receiving services reduces a household's need for services again in the future. Using the demographic information provided during hotline calls, researchers have developed models to predict the probability that a household will need services again within 2 years of being allocated a service. All households are assumed to have lower or equal probabilities of needing future services if given Transitional Housing than if given Emergency Shelter.

During the following activities you will be asked to see the same information that service providers receive and make decisions about how to allocate homeless services based on that information.

Training Block

Homeless service providers make decisions on which services to allocate to which households. These decisions are complex and based on complicated patterns of information about each household. Throughout this survey, you will be given information similar to what homeless service providers see when allocating services, and you will be asked to make decisions based on that information.

We will start with an example similar to what you will see in future tasks. You will see a total of 10 example households presented together in a table. As you proceed through this section, different households will be highlighted to show an estimate based on past administrative data of the likelihood of those households needing future services if given Transitional Housing or Emergency Shelter. Please read through these examples and estimates and spend some time looking for patterns in the data. Click "I Understand" when you are ready to proceed.

Here is a table of 10 examples of households needing homeless services. Each column in the table represents a different household and each row represents a piece of information that homeless service providers have when making decisions on which households should receive each kind of service. The next few screens will show the same table with the same ten households but will highlight the columns associated with households that have a certain predicted probability of needing future services if given either Transitional Housing or Emergency Shelter. Take a few minutes to familiarize yourself with each table and look for patterns in the information to help you categorize similar households later in the survey. Then, click "I Understand" when you are ready to proceed.

	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	2	1	1
Number of Children	0	0	0	0	0	0	0	1	0	0
Head of Household Gender	Female	Male	Male	Male	Female	Female	Male	Female	Female	Female
Head of Household Age	45	35	64	55	55	23	23	23	55	45
Head of Household Disabling Condition	No	Yes	Yes	No	Yes	No	No	No	No	No
Head of Household Receives Substance Abuse Services	No	No	No	No	No	No	Yes	No	No	No
Monthly Income	$800	$668	$1524	$400	$800	$367	$0	$1068	$800	$367
Number of Calls to Hotline	15	5	2	2	2	5	0	0	2	0
Prior Residence	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Transitional Housing	Private Emergency Shelter	Private Transitional Housing	Private Transitional Housing	Private Emergency Shelter

This is the same table presented previously. Models predict that the households highlighted in red have a **high** probability of needing services again within 2 years if they are given **Transitional Housing**.

	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	2	1	1
Number of Children	0	0	0	0	0	0	0	1	0	0
Head of Household Gender	Female	Male	Male	Male	Female	Female	Male	Female	Female	Female
Head of Household Age	45	35	64	55	55	23	23	23	55	45
Head of Household Disabling Condition	No	Yes	Yes	No	Yes	No	No	No	No	No
Head of Household Receives Substance Abuse Services	No	No	No	No	No	No	Yes	No	No	No
Monthly Income	$800	$668	$1524	$400	$800	$367	$0	$1068	$800	$367
Number of Calls to Hotline	15	5	2	2	2	5	0	0	2	0
Prior Residence	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Transitional Housing	Private Emergency Shelter	Private Transitional Housing	Private Transitional Housing	Private Emergency Shelter

This is the same table presented previously. Models predict that the households highlighted in yellow have a **medium** probability of needing services again within 2 years if they are given **Transitional Housing**.

	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	2	1	1
Number of Children	0	0	0	0	0	0	0	1	0	0
Head of Household Gender	Female	Male	Male	Male	Female	Female	Male	Female	Female	Female
Head of Household Age	45	35	64	55	55	23	23	23	55	45
Head of Household Disabling Condition	No	Yes	Yes	No	Yes	No	No	No	No	No
Head of Household Receives Substance Abuse Services	No	No	No	No	No	No	Yes	No	No	No
Monthly Income	$800	$668	$1524	$400	$800	$367	$0	$1068	$800	$367
Number of Calls to Hotline	15	5	2	2	2	5	0	0	2	0
Prior Residence	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Transitional Housing	Private Emergency Shelter	Private Transitional Housing	Private Transitional Housing	Private Emergency Shelter

This is the same table presented previously. Models predict that the households highlighted in green have a **low** probability of needing services again within 2 years if they are given **Transitional Housing**.

	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	2	1	1
Number of Children	0	0	0	0	0	0	0	1	0	0
Head of Household Gender	Female	Male	Male	Male	Female	Female	Male	Female	Female	Female
Head of Household Age	45	35	64	55	55	23	23	23	55	45
Head of Household Disabling Condition	No	Yes	Yes	No	Yes	No	No	No	No	No
Head of Household Receives Substance Abuse Services	No	No	No	No	No	No	Yes	No	No	No
Monthly Income	$800	$668	$1524	$400	$800	$367	$0	$1068	$800	$367
Number of Calls to Hotline	15	5	2	2	2	5	0	0	2	0
Prior Residence	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Transitional Housing	Private Emergency Shelter	Private Transitional Housing	Private Transitional Housing	Private Emergency Shelter

This is the same table presented previously. Models predict that the households highlighted in red have a **high** probability of needing services again within 2 years if they are given **Emergency Shelter**.

	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	2	1	1
Number of Children	0	0	0	0	0	0	0	1	0	0
Head of Household Gender	Female	Male	Male	Male	Female	Female	Male	Female	Female	Female
Head of Household Age	45	35	64	55	55	23	23	23	55	45
Head of Household Disabling Condition	No	Yes	Yes	No	Yes	No	No	No	No	No
Head of Household Receives Substance Abuse Services	No	No	No	No	No	No	Yes	No	No	No
Monthly Income	$800	$668	$1524	$400	$800	$367	$0	$1068	$800	$367
Number of Calls to Hotline	15	5	2	2	2	5	0	0	2	0
Prior Residence	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Transitional Housing	Private Emergency Shelter	Private Transitional Housing	Private Transitional Housing	Private Emergency Shelter

This is the same table presented previously. Models predict that the households highlighted in yellow are predicted to have a **medium** probability of needing services again within 2 years if they are given **Emergency Shelter**.

	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	2	1	1
Number of Children	0	0	0	0	0	0	0	1	0	0
Head of Household Gender	Female	Male	Male	Male	Female	Female	Male	Female	Female	Female
Head of Household Age	45	35	64	55	55	23	23	23	55	45
Head of Household Disabling Condition	No	Yes	Yes	No	Yes	No	No	No	No	No
Head of Household Receives Substance Abuse Services	No	No	No	No	No	No	Yes	No	No	No
Monthly Income	$800	$668	$1524	$400	$800	$367	$0	$1068	$800	$367
Number of Calls to Hotline	15	5	2	2	2	5	0	0	2	0
Prior Residence	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Transitional Housing	Private Emergency Shelter	Private Transitional Housing	Private Transitional Housing	Private Emergency Shelter

This is the same table presented previously. Models predict that the households highlighted in green have a **low** probability of needing services again within 2 years if they are given **Emergency Shelter**.

	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	2	1	1
Number of Children	0	0	0	0	0	0	0	1	0	0
Head of Household Gender	Female	Male	Male	Male	Female	Female	Male	Female	Female	Female
Head of Household Age	45	35	64	55	55	23	23	23	55	45
Head of Household Disabling Condition	No	Yes	Yes	No	Yes	No	No	No	No	No
Head of Household Receives Substance Abuse Services	No	No	No	No	No	No	Yes	No	No	No
Monthly Income	$800	$668	$1524	$400	$800	$367	$0	$1068	$800	$367
Number of Calls to Hotline	15	5	2	2	2	5	0	0	2	0
Prior Residence	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Transitional Housing	Private Emergency Shelter	Private Transitional Housing	Private Transitional Housing	Private Emergency Shelter

No Training Block

Homeless service providers make decisions on which services to allocate to which households. These decisions are complex and based on complicated patterns of information about each household. Throughout this survey, you will be given information similar to what homeless service providers see when allocating services, and you will be asked to make decisions based on that information.

We will start with examples similar to what you will see in future tasks. You will see a total of 10 examples presented together in a table. Read through the examples and try to think of the likelihood of those households needing future services if given Transitional Housing or Emergency Shelter. Click "I Understand" when you are ready to proceed.

Here is a table of 10 examples of households needing homeless services. Each column in the table represents a different household and each row represents a piece of information that homeless service providers have when making decisions on which households should receive each kind of service. Take a few minutes to familiarize yourself with the table and try to think of the likelihood of those households needing future services if given Transitional Housing or Emergency Shelter. Then, click "I Understand" when you are ready to proceed.

	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	2	1	1
Number of Children	0	0	0	0	0	0	0	1	0	0
Head of Household Gender	Female	Male	Male	Male	Female	Female	Male	Female	Female	Female
Head of Household Age	45	35	64	55	55	23	23	23	55	45
Head of Household Disabling Condition	No	Yes	Yes	No	Yes	No	No	No	No	No
Head of Household Receives Substance Abuse Services	No	No	No	No	No	No	Yes	No	No	No
Monthly Income	$800	$668	$1524	$400	$800	$367	$0	$1068	$800	$367
Number of Calls to Hotline	15	5	2	2	2	5	0	0	2	0
Prior Residence	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Emergency Shelter	Private Transitional Housing	Private Emergency Shelter	Private Transitional Housing	Private Transitional Housing	Private Emergency Shelter

Instructions Task 1

Next, we will present tables with descriptions of households seeking homeless services. Please use these descriptions to predict the probability that a household will need further services within 2 years if placed in Transitional Housing.
You will be presented with 10 households to sort into 3 groups: Low predicted probability, Medium predicted probability, and High predicted probability.

Task 1

Categorize the following households based on how likely you predict they are to need further services within 2 years if placed into Transitional Housing. Click on the household number label below the image to select your answer.

	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

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

Instructions Task 2

Now that you understand, we will present descriptions of households seeking homeless services in pairs. Please decide which household to prioritize for **Transitional Housing**.
You will be presented with 12 pairs of households.

Task 2 - Vignette Only Group

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	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

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	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

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	Household 2
Number of Household Members	1	1
Number of Children	0	0
Head of Household Gender	Male	Male
Head of Household Age	55	45
Head of Household Disabling Condition	No	Yes
Head of Household Receives Substance Abuse Services	No	Yes
Monthly Income	$0	$668
Number of Calls to Hotline	25	3
Prior Residence	Private Emergency Shelter	Private Emergency Shelter

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	Household 2
Number of Household Members	1	1
Number of Children	0	0
Head of Household Gender	Male	Male
Head of Household Age	45	45
Head of Household Disabling Condition	No	Yes
Head of Household Receives Substance Abuse Services	No	Yes
Monthly Income	$200	$0
Number of Calls to Hotline	25	5
Prior Residence	Private Emergency Shelter	Place not meant for habitation

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	Household 2
Number of Household Members	1	1
Number of Children	0	0
Head of Household Gender	Male	Male
Head of Household Age	45	45
Head of Household Disabling Condition	No	Yes
Head of Household Receives Substance Abuse Services	No	Yes
Monthly Income	$200	$0
Number of Calls to Hotline	25	5
Prior Residence	Private Emergency Shelter	Place not meant for habitation

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	Household 2
Number of Household Members	1	1
Number of Children	0	0
Head of Household Gender	Male	Male
Head of Household Age	45	35
Head of Household Disabling Condition	No	No
Head of Household Receives Substance Abuse Services	Yes	No
Monthly Income	$200	$0
Number of Calls to Hotline	2	25
Prior Residence	Private Emergency Shelter	Private Emergency Shelter

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	Household 2
Number of Household Members	1	3
Number of Children	0	2
Head of Household Gender	Female	Female
Head of Household Age	45	35
Head of Household Disabling Condition	No	Yes
Head of Household Receives Substance Abuse Services	No	Yes
Monthly Income	$400	$1524
Number of Calls to Hotline	0	25
Prior Residence	Place not meant for habitation	Unknown

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	Household 2
Number of Household Members	3	1
Number of Children	2	0
Head of Household Gender	Female	Female
Head of Household Age	23	35
Head of Household Disabling Condition	No	No
Head of Household Receives Substance Abuse Services	No	No
Monthly Income	$200	$0
Number of Calls to Hotline	5	0
Prior Residence	Private Emergency Shelter	Unknown

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	Household 2
Number of Household Members	3	1
Number of Children	2	0
Head of Household Gender	Female	Male
Head of Household Age	23	55
Head of Household Disabling Condition	No	Yes
Head of Household Receives Substance Abuse Services	No	Yes
Monthly Income	$1524	$0
Number of Calls to Hotline	3	2
Prior Residence	Private Emergency Shelter	Private Emergency Shelter

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	Household 2
Number of Household Members	2	1
Number of Children	1	0
Head of Household Gender	Female	Female
Head of Household Age	23	45
Head of Household Disabling Condition	No	No
Head of Household Receives Substance Abuse Services	No	Yes
Monthly Income	$3256	$200
Number of Calls to Hotline	25	0
Prior Residence	Unknown	Private Emergency Shelter

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	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

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	Household 2
Number of Household Members	5	1
Number of Children	4	0
Head of Household Gender	Female	Female
Head of Household Age	23	23
Head of Household Disabling Condition	No	No
Head of Household Receives Substance Abuse Services	No	No
Monthly Income	$668	$32
Number of Calls to Hotline	25	0
Prior Residence	Private Emergency Shelter	Private Transitional Housing

Task 2 - Vignette and Predictions Group

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	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
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

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	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
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

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	Household 2
Number of Household Members	1	1
Number of Children	0	0
Head of Household Gender	Male	Male
Head of Household Age	55	45
Head of Household Disabling Condition	No	Yes
Head of Household Receives Substance Abuse Services	No	Yes
Monthly Income	$0	$668
Number of Calls to Hotline	25	3
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

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	**Household 2**
Number of Household Members	1	1
Number of Children	0	0
Head of Household Gender	Male	Male
Head of Household Age	45	45
Head of Household Disabling Condition	No	Yes
Head of Household Receives Substance Abuse Services	No	Yes
Monthly Income	$200	$0
Number of Calls to Hotline	25	5
Prior Residence	Private Emergency Shelter	Place not meant for habitation
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

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	Household 2
Number of Household Members	1	1
Number of Children	0	0
Head of Household Gender	Male	Male
Head of Household Age	45	45
Head of Household Disabling Condition	No	Yes
Head of Household Receives Substance Abuse Services	No	Yes
Monthly Income	$200	$0
Number of Calls to Hotline	25	5
Prior Residence	Private Emergency Shelter	Place not meant for habitation
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

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	Household 2
Number of Household Members	1	1
Number of Children	0	0
Head of Household Gender	Male	Male
Head of Household Age	45	35
Head of Household Disabling Condition	No	No
Head of Household Receives Substance Abuse Services	Yes	No
Monthly Income	$200	$0
Number of Calls to Hotline	2	25
Prior Residence	Private Emergency Shelter	Private Emergency Shelter
Predicted probability of needing future services within 2 years if given Transitional Housing	Low	High
Predicted probability of needing future services within 2 years if given Emergency Shelter	Medium	High

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	Household 2
Number of Household Members	1	3
Number of Children	0	2
Head of Household Gender	Female	Female
Head of Household Age	45	35
Head of Household Disabling Condition	No	Yes
Head of Household Receives Substance Abuse Services	No	Yes
Monthly Income	$400	$1524
Number of Calls to Hotline	0	25
Prior Residence	Place not meant for habitation	Unknown
Predicted probability of needing future services within 2 years if given Transitional Housing	Low	High
Predicted probability of needing future services within 2 years if given Emergency Shelter	Medium	High

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	**Household 2**
Number of Household Members	3	1
Number of Children	2	0
Head of Household Gender	Female	Female
Head of Household Age	23	35
Head of Household Disabling Condition	No	No
Head of Household Receives Substance Abuse Services	No	No
Monthly Income	$200	$0
Number of Calls to Hotline	5	0
Prior Residence	Private Emergency Shelter	Unknown
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

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	Household 2
Number of Household Members	3	1
Number of Children	2	0
Head of Household Gender	Female	Male
Head of Household Age	23	55
Head of Household Disabling Condition	No	Yes
Head of Household Receives Substance Abuse Services	No	Yes
Monthly Income	$1524	$0
Number of Calls to Hotline	3	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

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	Household 2
Number of Household Members	2	1
Number of Children	1	0
Head of Household Gender	Female	Female
Head of Household Age	23	45
Head of Household Disabling Condition	No	No
Head of Household Receives Substance Abuse Services	No	Yes
Monthly Income	$3256	$200
Number of Calls to Hotline	25	0
Prior Residence	Unknown	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

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	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

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	Household 2
Number of Household Members	5	1
Number of Children	4	0
Head of Household Gender	Female	Female
Head of Household Age	23	23
Head of Household Disabling Condition	No	No
Head of Household Receives Substance Abuse Services	No	No
Monthly Income	$668	$32
Number of Calls to Hotline	25	0
Prior Residence	Private Emergency Shelter	Private Transitional Housing
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

Task 3 - Instructions for Efficient Group

Deciding who should receive a scarce resource like Transitional Housing is a complex task and there are different ways of prioritizing households.

Two possible prioritizations are:
1) **Efficient** - Give Transitional Housing to the households that would have the biggest benefit from being in Transitional Housing compared to Emergency Shelter
2) **Neediest First** - Give Transitional Housing to the households that would do worst in Emergency Shelter

For example:
Let Household 1 have a probability of reentry if given Transitional Housing of 70% and a probability of reentry if given Emergency Shelter of 90%.

Let Household 2 have a probability of reentry if given Transitional Housing of 30% and a probability of reentry if given Emergency Shelter of 70%

The **Neediest First** prioritization would give Household 1 Transitional Housing because with a probability of reentry of 90%, Household 1 is predicted to do worse in Emergency Shelter than Household 2

The **Efficient prioritization** would give Household 2 Transitional Housing because Household 2 gets a benefit of 40 percentage points (70 - 30) by moving from Emergency Shelter to Transitional Housing. Whereas Household 1 only gets a benefit of 20 percentage points (90 - 70).

Another example:
Let Household 1 have a probability of reentry if given Transitional Housing of 20% and a probability of reentry if given Emergency Shelter of 30%.
Let Household 2 have a probability of reentry if given Transitional Housing of 60% and a probability of reentry if given Emergency Shelter of 90%

The **Neediest First** prioritization would give Household 2 Transitional Housing because with a probability of reentry of 90%, Household 2 is predicted to do worse in Emergency Shelter than Household 1

The **Efficient prioritization** would also give Household 2 Transitional Housing because Household 2 gets a benefit of 30 percentage points (90 - 60) by moving from Emergency Shelter to Transitional Housing. Whereas Household 1 only gets a benefit of 10 percentage points (30 - 20).

Next, instead of descriptions of households, we will present only predictions based on past administrative data about whether households will need future services. These will again be presented pairs. Please decide which household to prioritize for Transitional Housing. You will be presented with 12 pairs of households.

Your goal is to make the most **efficient** assignment. As a reminder, an efficient assignment gives Transitional Housing to households that would have the biggest benefit from being in Transitional Housing compared to Emergency Shelter.

Task 3 - Instruction for Neediest Group

Deciding who should receive a scarce resource like Transitional Housing is a complex task and there are different ways of prioritizing households.

Two possible prioritizations are:
1) **Efficient** - Give Transitional Housing to the households that would have the biggest benefit from being in Transitional Housing compared to Emergency Shelter
2) **Neediest First** - Give Transitional Housing to the households that would do worst in Emergency Shelter

For example:
Let Household 1 have a probability of reentry if given Transitional Housing of 70% and a probability of reentry if given Emergency Shelter of 90%.
Let Household 2 have a probability of reentry if given Transitional Housing of 30% and a probability of reentry if given Emergency Shelter of 70%

The **Neediest First** prioritization would give Household 1 Transitional

Housing because with a probability of reentry of 90%, Household 1 is predicted to do worse in Emergency Shelter than Household 2

The **Efficient prioritization** would give Household 2 Transitional Housing because Household 2 gets a benefit of 40 percentage points (70 - 30) by moving from Emergency Shelter to Transitional Housing. Whereas Household 1 only gets a benefit of 20 percentage points (90 - 70).

Another example:
Let Household 1 have a probability of reentry if given Transitional Housing of 20% and a probability of reentry if given Emergency Shelter of 30%.
Let Household 2 have a probability of reentry if given Transitional Housing of 60% and a probability of reentry if given Emergency Shelter of 90%

The **Neediest First** prioritization would give Household 2 Transitional Housing because with a probability of reentry of 90%, Household 2 is predicted to do worse in Emergency Shelter than Household 1

The **Efficient prioritization** would also give Household 2 Transitional Housing because Household 2 gets a benefit of 30 percentage points (90 - 60) by moving from Emergency Shelter to Transitional Housing. Whereas Household 1 only gets a benefit of 10 percentage points (30 - 20).

Next, instead of descriptions of households, we will present only predictions based on past administrative data about whether households will need future services. These will again be presented pairs. Please decide which household to prioritize for Transitional Housing. You will be presented with 12 pairs of households.

Your goal is to make an assignment that gives the **neediest** households Transitional Housing. As a reminder, the neediest households are those who are predicted to do worst in Emergency Shelter.

Task 3 - Instruction for No Goal Group

Next, instead of descriptions of households, we will present only predictions based on past administrative data about whether households will need future services. These will again be presented pairs. Please decide which household to prioritize for **Transitional Housing**.
You will be presented with 12 pairs of households.

Task 3 - Questions

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	**Household 2**
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	Low

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

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

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	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	Low	Medium

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	**Household 2**
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

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	**Household 2**
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

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	Household 1	**Household 2**
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	High

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	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	Low	High

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

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

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

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

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

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

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	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

Which of the following households would you prioritize for Transitional Housing? Select your choice by clicking on the associated column in the image below.

	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	Medium	High

Demographics

What is your age?

What is the highest level of school you have completed or the highest degree you have received?

- Less than high school degree
- High school graduate (high school diploma or equivalent including GED)
- Some college but no degree
- Associate degree in college (2-year)
- Bachelor's degree in college (4-year)
- Master's degree
- Doctoral degree
- Professional degree (JD, MD)

Are you Spanish, Hispanic, or Latino or none of these?

- Yes
- None of these

Are you Spanish, Hispanic, or Latino?

- Spanish
- Hispanic
- Latino

Choose one or more races that you consider yourself to be:

- ☐ White
- ☐ Black or African American
- ☐ American Indian or Alaska Native
- ☐ Asian
- ☐ Native Hawaiian or Pacific Islander
- ☐ Other ____________

With which gender do you most identify?

- ○ Male
- ○ Female
- ○ Transgender Male
- ○ Transgender Female
- ○ Gender Variant/Nonconforming
- ○ ____________ Other
- ○ Prefer Not to Answer

Prior to your involvement in this study, how would you rate your familiarity with homelessness or homeless services?

- ○ Not at all Familiar
- ○ Slightly Familiar
- ○ Somewhat Familiar
- ○ Moderately Familiar
- ○ Extremely Familiar

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