When Do Citizens Resist The Use of AI Algorithms in Public Policy? Theory and Evidence

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Abstract

In recent years, there has been a significant rise in the use of algorithmic decision-making systems (ADS) to assist or replace human decision-making in a wide range of policy areas as policing, criminal sentencing, and social welfare assistance. How do citizens view the incorporation of this technology in guiding high-stakes decisions? I introduce a new theory to explain the conditions under which citizens view ADS as legitimate, fair, and accurate, and test it using data from original experiments embedded in a national U.S. survey. I show that across a wide range of policy domains, citizens exhibit aversion to the use of ADS in decisions that are seen as designed to sanction rather than to assist, and when they are required to make inferences about individuals rather than collectives. Evidence from a second experiment suggests that the employment of ADS in such contexts can significantly undermine the legitimacy of the policy actions they inform. Together, the study offers a framework to identify where AI-based tools will be deemed appropriate and where they might trigger backlash, highlighting the importance of accounting for citizens' values in AI development and implementation to maintain legitimacy and democratic accountability.

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The pre-analysis plan is available at https://osf.io/u7qs6/?show=view.

Introduction

In November 2020, Californians voted on a referendum to replace the state's policy of cash bail for pretrial release with an algorithmic risk assessment approach. Under the new law, local courts would determine whether individuals arrested and charged with a crime should remain in custody or be released while awaiting trial, based on an algorithmic assessment of the defendant's likelihood to appear in court, the seriousness of their offense, and their probability of recidivism (Pislar and Puleo, 2020). Despite evidence suggesting the algorithmic system could reduce crime among released defendants without increasing imprisonment rates (Kleinberg, Mullainathan, and Raghavan, 2016), voters decisively rejected the proposition by a wide margin (56% to 44%). What explains this opposition? Does the public response reflect a general resistance to the use of algorithms in governance, or is this resistance context-specific, reflecting particular concerns about using these tools in the criminal justice system?

These questions are particularly pertinent, given the growing use of algorithmic decision-making systems (ADS) in a wide array of policy contexts. In the last few years, government agencies and public authorities are increasingly relying on AI-based algorithms—software that autonomously makes assessments and predictions based on inferences from big data without explicit human instructions—to determine questions such as where to focus policing efforts, which child abuse allegations to investigate, who qualifies for public housing or how to allocate welfare benefits (e.g., Eubanks, 2018; Meijer, Lorenz, and Wessels, 2021; Robertson, Nguyen, and Salehi, 2021).

In this paper, I introduce a new theory to explain when citizens accept or reject ADS in governance, focusing on considerations of fairness and accuracy. I argue that these views are context-dependent and vary as a function of (1) the objective of the decision at stake, specifically whether it is seen as assisting or sanctioning, and (2) the population directly

affected by the decision: individuals versus collectives. I test this theory and its observable implications using novel data from two original, pre-registered experiments embedded in a nationally representative survey of the U.S. population.

The first experiment systematically examines individuals' perceptions of the appropriateness, fairness, and accuracy of ADS in governance by randomizing both the decision type and the policy domain in which the algorithm is employed. The results provide strong support for the theory: people exhibit aversion to ADS, particularly in decisions perceived as designed to sanction rather than assist, as well as when they require inferences about individuals rather than collectives. These findings are generalizable across a wide range of decisions and policy domains, including public education, immigration, social welfare, and criminal justice. The analysis also highlights the trade-off people face when considering the accuracy and fairness of ADS in decisions that assist individuals and those that sanction collectives. In these contexts, the weight given to each consideration follows the pattern predicted by the theory: respondents were less tolerant of ADS in sanctioning decisions, even when such systems were perceived to improve accuracy in decision-making.

While public opinion does not always shape policy, public approval of ADS in governance is crucial for maintaining legitimacy and democratic accountability. This is evident in recent high-profile cases where governments and municipalities have reversed or abandoned policies implemented by ADS due to public backlash. For example, both New Orleans and Los Angeles terminated their predictive policing programs following public outcry over racial bias and lack of transparency (Winston, 2018; Sainato and Chiu, 2021). Similarly, the UK's Department for Education withdrew its grade prediction algorithm amid protests over unfair treatment of disadvantaged students (Walsh, 2020), while in the Netherlands, public backlash against an algorithmic system for welfare fraud detection led to the government's resignation (International, 2021).

To empirically assess the political implications of public attitudes toward ADS in gov-

ernance, I present results from a second experiment that examines how algorithmic implementation affects overall policy support. By asking respondents to evaluate identical policy proposals while randomizing the decision-maker implementing the policy, I explore whether citizens actually care about the use of ADS and whether they consider it when evaluating policy issues. The results suggest that using ADS in contexts where citizens view them as inappropriate can undermine the legitimacy of the policy decisions and interventions they inform. Policy proposals involving sanctioning decisions, such as prioritizing child abuse investigations, received significantly less support when implemented algorithmically rather than by human officers. In contrast, the opposite pattern emerges for policies focused on assistance, particularly when they target collectives, such as allocating additional funding to certain schools. The results also imply that in cases where there is a tradeoff between considerations of fairness and accuracy, using algorithms as a supportive tool while keeping "humans in the loop" appears to be an attractive solution.

Overall, the study provides a useful framework to assess where AI-based tools will be deemed appropriate, might trigger backlash, and where combining algorithmic assessment with human judgment is most appealing. Beyond its practical implications, the findings contribute to the growing literature on the determinants of public opinion on AI and data-driven decision-making. Most of the experimental work on this matter focuses on the views and reactions of AI users or the operators who interact directly with AI algorithms and are able to choose whether and how to use their output (Lee, 2018; Waggoner and Kennedy, 2022). More recently, studies have shifted their focus to the general public, who are subjected to algorithmic decisions without the option to opt-out (Zhang and Dafoe, 2019; O'Shaughnessy et al., 2023). The findings presented in this paper add to the scant but rapidly growing research that underscores the contingent nature of mass attitudes (Araujo et al., 2020; Miller and Keiser, 2021; Schiff, Schiff, and Pierson, 2021; Schiff et al., 2023; Wenzelburger and Achtziger, 2023). By showing how the perceived fairness and accuracy of the same algo-

rithmic system can vary depending on the type of decision they inform, this study provides more nuanced and systematic insights that transcend various policy areas.

More broadly, the study speaks to the growing work on the political ramifications of the recent advancements in AI and digitization, which has primarily focused on labor market disruptions (e.g., Gallego and Kurer, 2022). The study provides insights into an important yet under-explored domain where AI-based technology increasingly shapes citizens' lives and their interactions with government agencies, carrying substantial implications for democratic governance. It, therefore, underscores the need for a more comprehensive research agenda in political science, examining citizens' values, expectations, and concerns regarding the use of AI in governance and exploring ways to integrate these perspectives into AI governance frameworks.

Contextual Attitudes Toward Using AI Algorithms in Governance

The integration of ADS in high-stake policy domains has sparked a debate about the potential benefits and risks (Schiff et al., 2020). Proponents contend that as algorithms provide data-driven analysis on a scale, scope, and time frame that humans cannot offer, they can help deploy government resources and public services more efficiently, objectively, and accurately (Lepri et al., 2018). However, recent research has cast doubt on this idea, highlighting a range of ethical concerns, including racial bias, discrimination against marginalized groups, the perpetuation of societal inequities, a lack of transparency and accountability, and privacy violations (e.g., Barocas, Hardt, and Narayanan, 2017).

Much of this debate centers on whether ADS can enhance or diminish accuracy and fairness in decision-making. Accuracy, in this context, refers to the extent to which the algorithm achieves its intended outcomes, such as correctly identifying individuals likely to recidivate or students with learning difficulties. Fairness, on the other hand, is more elusive. It includes procedural aspects, such as neutrality, consistency, and transparency (Tyler,

2006), which may overlap with accuracy when reducing bias results in decisions that are both fairer and more accurate. However, it also involves more substantive aspects that go beyond accuracy, such as ensuring equal opportunities and accountability (Reich, Sahami, and Weinstein, 2020). The latter relates to the consequences of the decisions, specifically, the extent to which they affect or constrain citizens' lives.

How do citizens evaluate the fairness and accuracy of ADS? Most of the empirical work assumes that people's views of algorithms are quite fixed, determined either by their predispositions toward the technology (Dietvorst, Simmons, and Massey, 2018; Zhang and Dafoe, 2019) or their prior knowledge about AI (Horowitz and Kahn, 2024). Other research emphasizes the design features of the technology, such as the quality or amount of data the algorithm is trained on or its degree of transparency (Waggoner et al., 2019; Kennedy, Waggoner, and Ward, 2022). Recent studies have shown that individuals' evaluations of ADS vary depending on the context it is used (Horowitz, 2016; Lee, 2018; Logg, Minson, and Moore, 2019; Araujo et al., 2020). Building on this contextual evidence, I argue that individuals' expectations and assumptions about the accuracy and fairness of using ADS in governance depend significantly on two key features of the decision.

The first dimension relates to the target of the decision, namely, the population that the decision directly affects. In particular, I distinguish between decisions that target *individuals*—such as whom to stop for speeding or whom to provide with social benefits—and decisions that target *collectives* (i.e., groups or areas), such as which neighborhoods to patrol or which schools should receive further funding assistance.

The second dimension relates to the decision's objective, particularly whether it seems designed to sanction or benefit. *Assisting* decisions involve providing social services or public goods, such as determining where to build a new public park or who is eligible for public housing. Conversely, *sanctioning* decisions involve imposing penalties or restrictions on targeted groups or individuals, such as increasing law enforcement against illegal immigration

or removing a child from their parent's care.

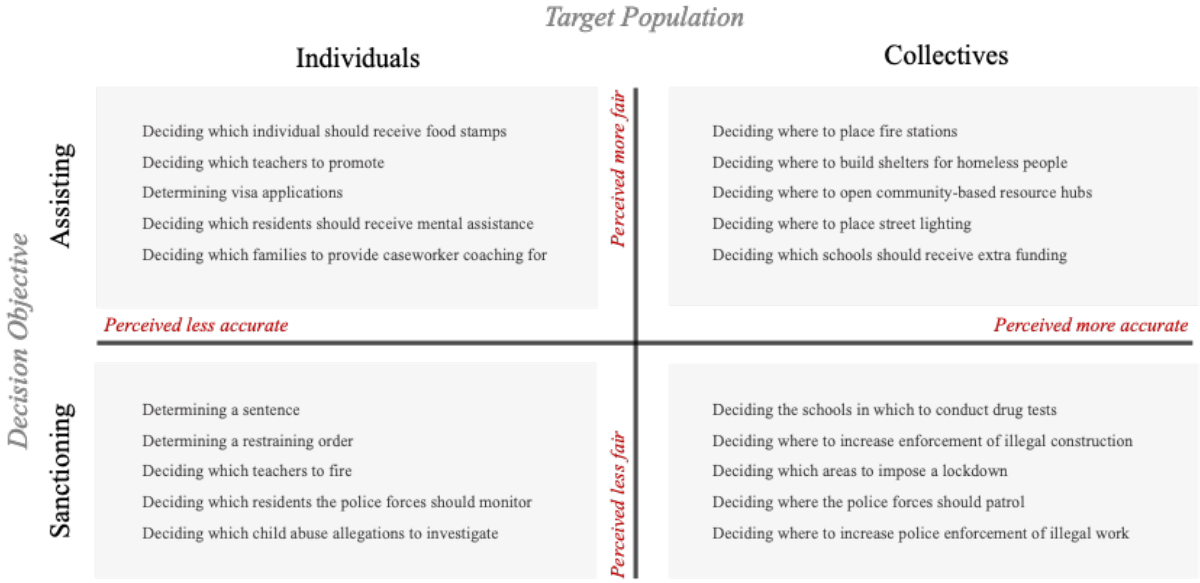
The distinction between assisting and sanctioning decisions is not always clear-cut. One could argue that determining eligibility for a social benefit or resource can be viewed as sanctioning rather than assisting. However, the theory assumes that there is a fundamental difference between decisions that "do not give" (assisting) and those that "take away" (sanctioning). The difference is derived from the potential change in the status quo, which has implications for the decision's consequences, particularly the extent to which the decision outcome is reversible.[1] Drawing on Berlin (1969)'s classical distinction between negative and positive liberty, sanctioning decisions directly constrain an individual's choices and behaviors, thus impacting their negative liberty - their freedom from external constraints. In contrast, assisting decisions influence the conditions and resources that enable individuals or groups to pursue their goals, relating to their positive liberty - their capacity to act. This distinction has important implications for the reversibility and lasting consequences of these decisions.

To validate this theoretical framework, I conducted a survey on MTurk, asking 150 respondents to categorize six randomly selected decisions into the four types derived from the theory, saying nothing about the identity of the decision maker. The results, reported in Figure A-4, show that respondents' answers are significantly consistent with this two-by-two classification.

Although the two dimensions are not all-encompassing, they provide a useful starting point for understanding contextual variation in preferences. As Figure 1 shows, there are many examples of real-world decisions in the public sector that can be classified into this two-by-two framework.

[1] Building on this framework, further study should examine these distinctions as a spectrum, where, for example, some decisions may be perceived as more assisting than sanctioning. Another useful direction is to study heterogeneity across individuals in classifying policy decisions, which could affect their views on using ADS in these contexts.

Figure (1) Four Types of Decisions in Public Policy



Notes: This figure applies the theoretical framework to real-world examples. 1

I contend that ADS are more likely to be seen as improving accuracy when applied to collectives rather than individuals, as they excel at processing large amounts of data but may overlook individual nuances and exceptional circumstances that human judgment and discretion can better address. In terms of fairness, the impersonal nature of ADS may be perceived as an advantage in assisting decisions that distribute benefits, as it reduces the risk of favoritism and corruption associated with human decision-makers. However, this same impersonality can make algorithms appear less fair when used in sanctioning decisions which have less reversible consequences. In these contexts, human accountability and reasoning are deemed more important for ensuring fairness. In what follows, I characterize each of the four decision types in terms of accuracy and fairness and derive observable implications for the perceived legitimacy of using ADS in each of the four decision types.

1. Assisting collectives

In terms of accuracy, the fact that algorithmic systems rely on big data to make predictions about aggregate cases can be perceived as highly accurate, especially compared to the limited ability of humans to capture, aggregate, and process such a massive amount of information (Green and Chen, 2019). Indeed, research suggests that people view algorithms relying on big data as inherently trustworthy, using this 'big data effect' as a heuristic to gauge the algorithm's quality (Waggoner et al., 2019).

Assuming that algorithms make decisions based on rules applied consistently over time and across different parties and situations, several studies suggest that such technology has the potential to increase not only accuracy but also fairness in human decision-making (e.g., Helberger, Araujo, and Vreese, 2020).

In addition to accuracy, algorithms are often seen as promoting fairness by applying consistent, impersonal procedures over time and across different cases (e.g., Sunstein, 2019). This consistency is particularly valuable in distributive decisions, which often involve allocating benefits to specific groups or communities. Such decisions, as Lowi (1964) notes, tend to be made in isolation from broader policy frameworks. They typically focus on short-term gains for particular groups while deferring broader societal costs that are less immediate and visible. This isolated nature of distributive decisions increases the risk of favoritism and corruption in human decision-making, making the impartiality of algorithms especially appealing.

Taken together, when people form judgments about the use of ADS in decisions of this kind, they are not expected to perceive meaningful tradeoffs between accuracy and fairness considerations. The upper right panel of Table 1 indicates that the use of algorithms is expected to improve both accuracy and fairness in decision-making designed to assist collectives.

2. Sanctioning collectives

For the same reasons noted in the context of assisting, data-driven algorithms appear to be highly accurate in locating areas or communities likely to face major challenges. Nonetheless, using these assessments and predictions–as accurate as they may be–to sanction and punish targeted communities rather than assist them with the resources they need can be perceived as unfair in some substantive respects.[2]

The key concern is that using ADS for sanctioning purposes can have a long-lasting impact and may adversely affect historically disadvantaged groups, thereby undermining equality of opportunity. Unlike decisions that assist collectives, where ADS can potentially promote equality of outcomes by redressing or compensating communities or areas suffering from past injustices, using these data-driven assessments to sanction groups could reflect and therefore perpetuate such injustices (Barocas, Hardt, and Narayanan, 2017).

A growing concern in this context is that ADS could lead to feedback effects in the sense that they not only predict events but also contribute to their future occurrence (Brayne and Christin, 2021). Consider, for example, the predictive policing algorithm widely used by U.S. police departments to assign patrols. This algorithmic system relies on linkages between locations, events, and historical crime rates to predict the areas where crimes are most likely to occur in the future. This can lead to a negative feedback loop in which police disproportionately patrol areas with historically high crime rates, resulting in more arrests in those locations, which then become the algorithm's new training data, confirming and reinforcing its earlier predictions (Ferguson, 2017).[3]

The key point here is that the same algorithmic system, which assesses the risk of crime

[2]Indeed, recent studies in international relations document cases of public support for using ADS in national security decisions targeting collectives (Horowitz and Kahn, 2024), particularly for defense, but less so for offensive purposes (e.g., autonomous weapons systems) (Horowitz et al., 2023)

[3]The concern that algorithmic systems not only predict future events but also shape the conditions they are designed to predict aligns with policy feedback theory, which posits that by distributing resources, policies can shape political behavior over time (Pierson, 1993).

in a particular area, may be perceived as fair in decisions that assist collectives (e.g., deciding where to put more streetlights or where to build a community-based resource center) but significantly unfair in decisions that sanction collectives (e.g., deciding the schools in which to conduct more drug and alcohol testing).

The observable implication is that using ADS for decisions that sanction groups involves a potential tradeoff: it may be seen as more accurate but also as unfair. Since these are highly consequential decisions, I expect that fairness considerations will outweigh accuracy considerations and thus trigger greater opposition to ADS in this context.

3. Assisting individuals

The main characteristic of decisions that assist individuals is that they are usually made at the "street-level bureaucracy," a term that refers to the layer of bureaucracy, including judges, teachers, social workers, and police officers, that directly interacts with citizens and makes everyday decisions (Lipsky, 1980). These decisions often involve nuances or extenuating circumstances, making it impossible to prescribe (and thus code) a correct response ahead of time for all cases and situations.

Human bureaucrats can flexibly refine the contours of their decision boundaries before deciding on a novel or marginal case. Yet for algorithms that aggregate data, such reflexivity can only occur *after* the system has received feedback or additional training data, and more importantly, after an incorrect decision has occurred (Binns, 2019). Data-driven algorithms are, by their nature, simplifications that cannot account for all possible relevant facts about subjects and thus necessarily treat people as members of groups rather than as individuals (Brauneis and Goodman, 2018). Consequently, due to their difficulty in identifying borderline and exceptional cases, algorithms may be perceived as less accurate than humans in making decisions about individuals.[4]

[4]Note that this heightened concern about individual-level accuracy reflects laypeople's intuitions and may not always align with the logic of statistics or expert opinions. The idea is that people are more aware of, and

The very discretion that allows humans to tailor decisions to unique situations can also lead to potential misuse–whether intentional or not–based on personal biases, favoritism, or other irrelevant factors (Danziger, Levav, and Avnaim-Pesso, 2011; Alkhatib and Bernstein, 2019). The rule-based, data-driven approach of ADS ensures that all individuals are treated equally under the same criteria and, therefore, can be perceived as fair from a procedural standpoint.

Taken together, people are expected to weigh a trade-off between accuracy and fairness when evaluating the use of ADS in assisting individuals. As I will show, since the repercussions of these decisions on individuals' lives and opportunities are more reversible than those in sanctioning decisions, people might be more willing to accept the use of ADS, balancing the potential loss in accuracy with gains in procedural fairness.

4. Sanctioning individuals

As with decisions that assist individuals, the inability of algorithms to adapt to novel or marginal circumstances is expected to lead people to perceive them as less accurate when sanctioning individuals (Young, Bullock, and Lecy, 2019).

In terms of fairness, the black box nature and inherent opacity of ADS, which makes it difficult to explain their output, even for programmers, also makes it difficult for ordinary citizens to access and challenge their decisions (Pasquale, 2015). Such access, though, is necessary to ensure accountability in decision-making, namely, the notion that the decision maker is obligated to explain and justify a decision to the subjects to whom the decision relates. A lack of accountability is expected to produce a strong sense of unfairness, especially in decisions of this type, as any potential error would be highly significant both for an individual's life (e.g., a false positive that wrongfully convicts an innocent person) and for

therefore worry more about, idiosyncratic elements when decisions are granular. Such individual variances are perceived to be averaged out at the aggregate level, thereby raising fewer concerns in the context of collective decisions.

Table (1) Classifying attitudes toward ADS in the public sector

		Target Population	
		Individuals	Collectives
Objective	Assisting	*(1)* *Trade-off:* *AI less accurate but fairer than humans*	*(2)* *No trade-off:* *AI more accurate and fairer than humans*
		Reversible outcomes	
	Sanctioning	*(3)* *No trade-off:* *AI less accurate and less fair than humans*	*(4)* *Trade-off:* *AI more accurate but less fair than humans*
		Less reversible outcomes	

society's safety (e.g., a false negative that exonerates a guilty individual).

Returning to the example that opened this paper–the proposal to replace California's cash bail system with an algorithmic risk assessment tool. As in Kafka's novel *The Trial*, in which the protagonist Josef K. is arrested, charged, sentenced, and ultimately punished without knowing the charges or meeting the prosecutor, ADS could place individuals in a similarly Kafkaesque position in which they feel they are at the mercy of an entity they do not understand, and whose decisions are not transparent or explained. Accordingly, as shown in the lower right panel of Figure 1, for sanctioning decisions that have less-reversible repercussions for the lives and liberties of individuals, I expect that people on average view ADS as both less fair and less accurate compared to other contexts.

In summary, Table 1 outlines the characteristics of each type of decision, focusing on accuracy, fairness, and the potential trade-offs between them. The table suggests that citizens, on average, are likely to view ADS as both fair and accurate when used for decisions that assist collectives. However, they are expected to perceive these systems as less fair and accurate when applied to sanction individuals. Moreover, when accuracy and fairness conflict, citizens are likely to prioritize retaining human decision-makers who can exercise discretion, particularly in decisions with less reversible consequences. As a result, they may show lower tolerance for the use of ADS in such contexts. The following sections empirically evaluate these theoretical expectations.

Research Design

To test the theoretical predictions, I designed two original experiments embedded in a nationally representative survey administered to American adults. The sample consisted of 1,590 adults, recruited in March–April 2022 by the survey company Dynata (formerly Survey Sampling International - SSI), which is commonly used in social science research (Malhotra, Monin, and Tomz, 2019; Read, Wolters, and Berinsky, 2021). SSI used quota sampling to approximate the U.S. adult population with respect to gender, age, education, and race/ethnicity. Table A-1 in the Appendix shows the characteristics of the sample compared with those of the general U.S. population. The table indicates that the sample is representative along the quota dimensions. For more details about the sample see Appendix A.

The survey includes two experiments. The *Decision Type Experiment* directly tests the theory by asking respondents to evaluate the appropriateness of ADS across different policy contexts, randomizing the type of decision along two the theoretical dimensions. The *Policy Evaluation Experiment* examines the political implications of these views by asking respondents to evaluate identical policy proposals, randomizing the decision-maker who implements the policy. Figure 2 illustrates the flow of the survey design. Respondents participated in all experiments, but treatment assignment in each experiment was independent.[5]

To ensure respondents have a similar definition of a predictive algorithm in mind, the following description was provided at the beginning of the survey: "A predictive algorithm is a computer software that makes decisions without human instruction, relying on a massive amount of data." To reduce concerns about experimenter demand effects, I communicated

[5]Although the Decision Type Experiment provides the primary test of the theory and is discussed first in the manuscript, it was placed at the end of the survey. Presenting the Policy Evaluation Experiment first ensures respondents focus on the substantive merit of the policy proposals without being primed to inevitability think about the decision-maker implementing the policy. This design provides a fairer test of whether people naturally consider the use of ADS when assessing policy issues. Table A-18 in the Appendix shows that the results from the Decision Type experiment remain the same when controlling for the treatments received in the Policy Evaluation Experiment.

this definition indirectly, along with two other definitions relevant to the survey.[6]

Decision Type Experiment

The *Decision Type Experiment* directly tests the theory by examining contextual variation in people's views on the use of ADS in public policy implementation across various policy domains and issue areas. Respondents were presented with a matrix of several randomly selected policy decisions and were asked to evaluate the appropriateness and, in a follow-up question, to assess the perceived accuracy and fairness of using ADS in each decision. The matrix includes two components.

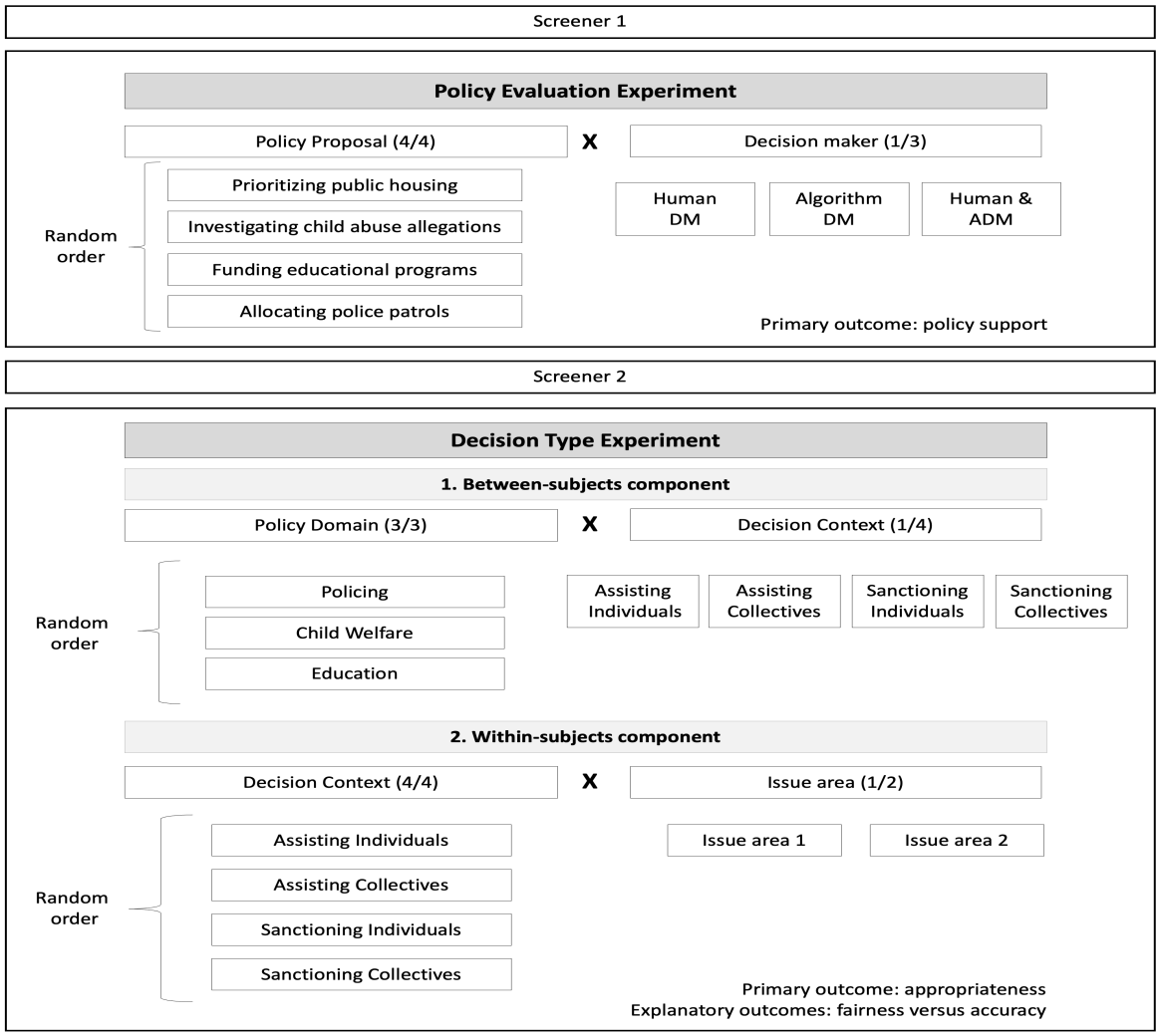
Between-Subject Component. Respondents first evaluate decisions from three high-stakes policy domains: policing, education, and child welfare, presented in a random order on the same matrix. Each policy domain was independently randomized along two theoretical dimensions: (1) whether the decision assists or sanctions and (2) whether the decision targets individuals or collectives.[7] Table 2 provides the wording of the questions by policy domains.

Within-subject component. Respondents were presented respondents with four additional items on the same matrix, each corresponding to a different decision type: assisting individuals, assisting collectives, sanctioning individuals, and sanctioning collectives. For each decision type, the issue area was randomly assigned to one of two issue areas to en-

[6]This item was also used as a screener. On the next page, respondents were presented with four definitions and asked to indicate which one did not appear on the previous page. Those who failed to answer correctly were immediately removed from the study before the randomization to the first experiment. The survey included an additional screener question before the second experiment. The question asked: "People are very busy these days and many do not have time to follow what goes on in the government. We are testing whether people read questions. To show that you've read this much, answer both 'extremely interested' and 'very interested."' Only respondents who passed both pre-treatment screeners completed the full survey and were included in the analysis. Furthermore, I incorporated an additional non-screening attention check within the matrix of the decision type experiment, which asked respondents the following: "It's important that you pay attention to this study, please tick 5."

[7]Notably, while each respondent evaluated all three policy domains, the specific decision type was independently randomized for each domain.

Figure (2) Survey Design



Notes: Figure 2 shows the sequence of the experiments embedded in the survey, the randomization procedures taken within each experiment, and the outcomes included in each experiment.

hance the broad applicability of the theory across various relevant policy decisions. For example, all respondents were asked to evaluate the use of ADS in one out of two decisions that sanction individuals: either deciding sentencing based on a prediction of the individual's risk of committing a future crime, or deciding to issue a restraining order based on a prediction of the individual's risk of assaulting their partner.[8] Rather than isolating the effect of a specific policy issue, this component aimed to assess a systematic variation within individuals across the four decision types, while covering a wider range of policy interventions and issue areas beyond those used in the first component. In that sense, this component provides additional correlational evidence that complements the primary between-subject component.[9]

Balance tests, as shown in Table A-5, confirm that all conditions are balanced across key demographic covariates, including gender, race, age, educational attainment, and technological literacy (see Appendix A for measurement details). To account for potential spillover effects, I randomized the order of the items presented to respondents within each matrix component.[10] Table A-7 shows the results remain robust when controlling for order effects.

The primary outcome of interest is the perceived appropriateness of using algorithmic rather than human decision-making across various contexts. This measure captures citizens' general acceptance or rejection of algorithmic governance. The wording for the question reads as follows: "We ask that you read the description of several policy decisions. For each please indicate how appropriate it is to have that decision made by an algorithm rather than by a

[8] See Table A-2 for question and treatment wordings.

[9] Ideally, both the decision type of decision and the policy domain would have been fully randomized across all decisions within and between subjects. However, finding comparable real-world examples for each of the four decision types within the same policy domains proved difficult beyond the three high stakes domains included in the first compoenent. Still, there is a wide range of other relevant cases in which ADS are being used that are worth examination but are not fully comparable across domains or types of decisions. The within-subject component addressed this tradeoff between internal validity and the desire for a broader policy scope.

[10] By asking first about all three policy domains, the experiment incentivizes respondents to compare ADS across policy domains rather than to focus on differences in the type of decision within domains as the theory predicts. This approach thus provides a hard test for the theory.

human being," with answers ranging on a seven-point scale from 1 "extremely appropriate" to 7 "extremely inappropriate."[11] As preregistered, I dichotomized this variable to facilitate the interpretation of the results in a clear and politically substantive way. The variable is coded as 1 for respondents who found the use of ADS appropriate (above the middle "indifferent" category) and 0 otherwise. This approach allows me to estimate the proportion of the population open to ADS use in a clear and politically meaningful manner.[12]

To test the specific mechanisms proposed by the theoretical framework, the study includes follow-up questions about the perceived accuracy and fairness of algorithmic systems in each decisions they were presented with earlier. Respondents rated the *fairness* and *accuracy* of ADS in each of the previous decisions on a seven-point scale ranging from "extremely inaccurate/unfair" (1) to "extremely accurate/fair" (7). These two questions were presented side-by-side in the same matrix and in randomized order to minimize potential order effects. To estimate the proportion of the population that perceived ADS as accurate or fair, I dichotomized these variables, assigning a value of '1' if the respondent chose any of the three categories above the midpoint on the scale and '0' otherwise.[13]

Results: Effect of Decision Type on perceived appropriateness

To evaluate the theoretical predictions, I first examine how the perceived appropriateness of ADS in governance varies across policy contexts depending on the type of decision, specifically whether it is designed to assist vs. sanction and whether it targets individuals vs. collectives. To this end, I begin with analyzing data from the between-subjects component,

[11] I intentionally avoided using the term "legitimate" in the question due to its strong legal connotations, which could influence respondents to consider the legality of ADS uses rather than their personal judgment and sense of right and wrong.

[12] The binary coding approach was chosen to capture potential shifts among respondents who might not have strong initial opinions regarding the delegation of policy decision making to Al-based systems. Table A-7 reports results using alternative cut-off points or the full seven-point scale, confirming that the main effects remain statistically significant and substantively similar.

[13] See Tables A-3 and A-11 for summary statistics of the three outcomes.

Table (2) Decision Wordings Randomized in the Between-Subjects Component

	Assisting	Sanctioning
Public Education		
Individuals	Deciding which teachers to promote based on an assessment of their effectiveness in improving students' grades.	Deciding which teachers to fire based on an assessment of their effectiveness in improving students' grades.
Collectives	Deciding which schools should receive extra funding for alcohol and drug education programs, based on the risk of juvenile crime in that area.	Deciding at which schools to conduct drug and alcohol tests, based on an assessment of the risk of juvenile crime in that area.
Policing		
Individuals	Deciding which residents should receive certain social services and mental health assistance, based on an assessment of their likelihood of shooting someone with a gun.	Deciding which residents the police forces should monitor, based on an assessment of their likelihood of shooting someone with a gun.
Collectives	Deciding where to place street lighting, based on an assessment of the risk of crime in the area.	Deciding where the police forces should patrol, based on an assessment the risk of crime in the area.
Child Welfare		
Individuals	Deciding where to open community resource centers, based on an assessment of the risk of child abuse and neglect in neighborhoods.	Deciding where police forces should increase enforcement, based on an assessment of the risk of child abuse in neighborhoods.
Collectives	Deciding which families to provide caseworker coaching and mental health services, based on an assessment of the risk of child abuse.	Deciding which child abuse allegations to investigate, based on an assessment of the risk of child abuse.

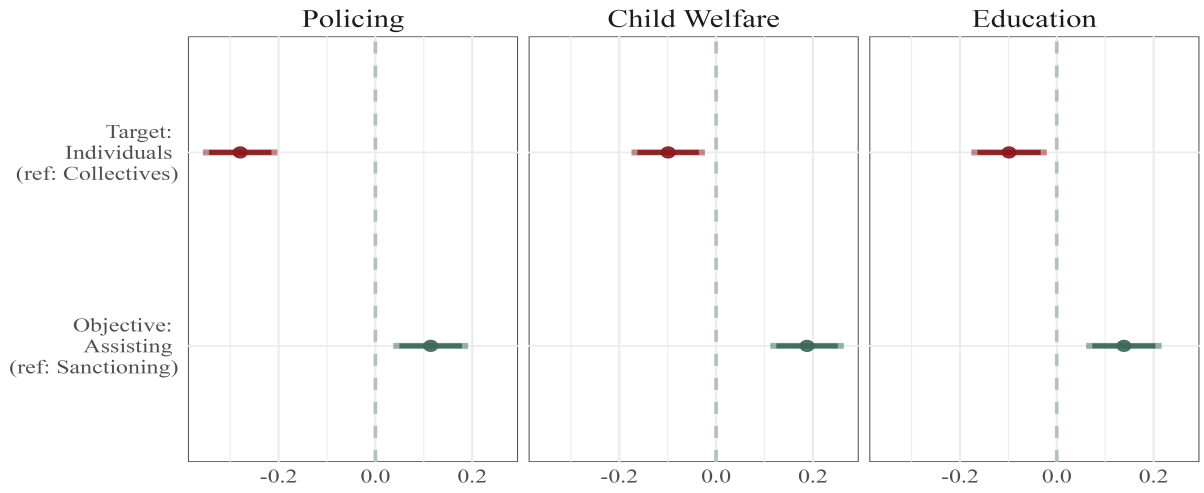
Notes: This table details the treatment conditions included in the between-subject experiment. Respondents received decisions from three policy domains, each independently randomized into one of the four types of decisions.

which independently manipulates these two dimensions within three distinct policy domains: policing, education, and child welfare. For each domain, I calculate the average treatment effects (ATEs) of the two dimensions.[14]

Figure 3 presents estimates from linear three probability models (LPM) studying the effect of the two theoretical dimensions on the probability of finding the use of ADS appropriate in each policy area: education, policing, and child welfare. To minimize order effects, the analysis uses data from the first item randomly presented to respondents. Results are reported in columns 1, 4, and 7 of Tables A-6. To enhance statistical power, Table A-7 replicates the results using pooled data from all policy domains and controlling for the presentation order of the items. Table A-9 confirms that all results remain substantively similar when using a multilevel analysis that accounts for both between and within-subject

[14]The mean value of the three dependent variables and associated confidence interval by the four types of decisions are reported in Table A-4.

Figure (3) Effects of decision type on perceived appropriateness of ADS, across domains



Notes: The figure shows marginal effects estimated separately for each policy area: education, child welfare, and policing, using data collected from the first item randomly presented to respondents. The dependent variable takes the value of '1' if the respondent indicates that it is appropriate to use ADS in this area and '0' otherwise. The independent DV are indicators for the context of the decision: the target of the decision and its objective. Base categories are decisions on collectives and decisions that sanction. The full analysis can be found in Table A-6, specifically in columns 1, 4 and 7.

variation.

Consistent with the theory, the results show that people are distinctly less tolerant of ADS when they target individuals rather than collectives. This negative effect is statistically significant and substantively meaningful across all three policy areas ($p< 0.05$). For example, in child welfare, using an algorithmic system to assess the risk of child abuse in a specific family instead of a neighborhood significantly decreases the probability of viewing such use as appropriate by 10 percentage points.

When looking at the objective of the decision, Figure 3 shows that ADS face significantly less opposition when used for assistance rather than sanctioning. Across all three policy domains, respondents were significantly more likely to view ADS as appropriate when implementing assisting rather than sanctioning decisions ($p< 0.001$). As Table A-6 shows, the estimates are statistically significant across policy domains, ranging from 11 percentage

points in policing to 19 percentage points in child welfare. The results are also substantively large. For instance, in public education, an algorithmic system assessing teachers' effectiveness in improving students' grades was accepted by only 15 percent of respondents when used to decide which teachers to *fire*, compared to 34 percent when used to decide which teachers to *promote*.

I conducted a set of tests to confirm the robustness of the findings. As Table A-6 shows, controlling for demographic characteristics, such as age, gender, education, and race, and other attitudinal covariates, such as technological literacy or prior knowledge of AI, does not alter these results. Tables A-7 and A-8 confirm that the results remain consistent when using logistic regression or alternative measures of the outcome. Moreover, to ensure that respondents were attentive to the treatments, I measured the response time for each question (Read, Wolters, and Berinsky, 2021). As table A-8 shows, the findings are robust when controlling for both fast, likely inattentive respondents who rush through surveys and very slow respondents who may be distracted and exhibit longer response times. [15] The results also hold when controlling for inattentive respondents using the non-screening attention check embedded within the same matrix of the experiment.

To confirm the generalizability of these findings beyond the specific items used in the between-subjects component, I analyze data from the within-subject component, which covers a wider range of issue areas, including decisions about restraining orders, criminal sentences, providing food stamps, study assistance, allocating shelters for the homeless, fire stations, enforcing illegal instructions, and illegal work. I employed an LPM regressing a binary outcome for the perceived appropriateness of using ADS on indicator variables for the two theoretical dimensions, as well as their interaction term, while controlling for the issue area and using fixed effects for respondent. The results, reported in Table A-13, are highly consistent with the main findings and further support for the theory, showing a robust

[15] This analysis was not pre-registered.

association between the type of decision and the perceived appropriateness of using ADS in this range of other policy areas and cases. Once again, ADS is significantly less likely to be deemed appropriate in decisions involving sanctions rather than assistance ($p < 0.01$) and in decisions applying to individuals rather than collectives ($p < 0.01$). Again, results are of a similar magnitude when using the alternative outcome measure (columns 2 and 4), and when using a linear mixed model with random intercepts for different policy issues and for each respondent (columns 4-6).[16]

Additional Results: Fairness-Accuracy Trade-offs

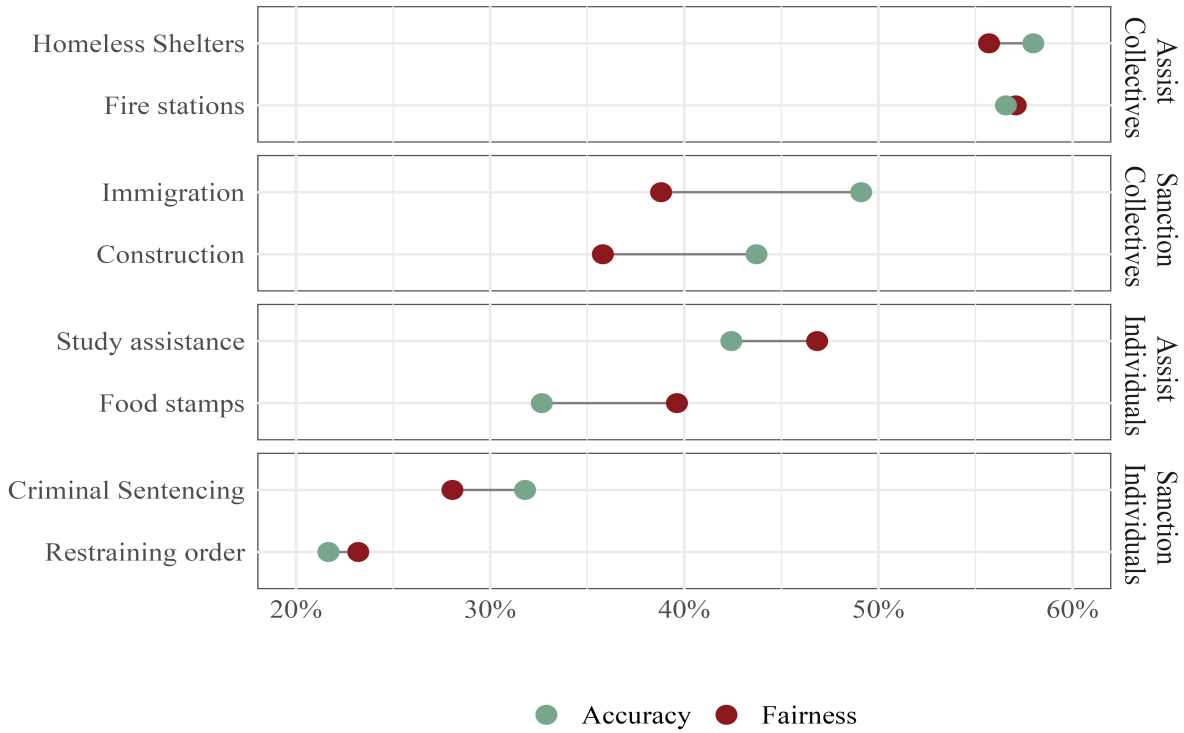
The results indicate that public opinion on ADS in government varies across and within policy domains, depending on (1) the decision's target and (2) its objective. Respondents are more likely to find ADS appropriate for assisting rather than sanctioning decisions and when targeting collectives rather than individuals. Indeed, using ADS to inform decisions assisting collectives received the highest acceptance rate, while using ADS in decisions sanctioning individuals received the lowest share.[17] The theory explains this variation by considering individuals' expectations about the perceived accuracy and fairness of ADS and the potential trade-offs between these considerations in two other types of decisions: assisting individuals and sanctioning collectives. To explore these mechanisms, I turn now to examine the perceived fairness and accuracy of using ADS in each of the four decision types using data from the within-subject component. Figure 4 compares the share of respondents who deem ADS use fair with those who regard it as accurate, for each decision type and issue area. Table A-14 formally tests these differences using paired t-tests.

First, consistent with the main results, ADS are seen most favorably when used to assist

[16] While findings show systematic variation in citizens' views of ADS as a function of target and decision objective, as the theory predicts, this does not exclude the possibility that policy domains independently account for some of the remaining unexplained variations in attitudes. Theorizing and testing mechanisms through which policy domains shape these attitudes is a promising avenue for future research.

[17] See Tables A-4 and A-12 for the full descriptive results.

Figure (4) Perceived Fairness versus Accuracy, by Decision Type and Issue Area



Notes: This figure shows the share of respondents who evaluate ADS as accurate (green dots) compared to the share of respondents who evaluate it as fair (red dots), across the four decision types and issue areas included in the within-subject component.

collectives such as determining the location of a new fire station or homeless shelter. In this context, ADS received the highest ratings on both fairness and accuracy, with no significant trade-off between the two. Similarly, there is minimal trade-off between fairness and accuracy when ADS are used to sanction individuals (p=0.264).[18] The bottom panel shows that in both issue areas—criminal sentencing and restraining order—the shares of respondents who perceived ADS to be fair and accurate do not exceed 22%-32%– about 26-34% lower than when ADS used in decisions assist collectives (p< 0.01).[19] This finding is notable given that

[18]This result is based on a paired t-test comparing averaged shares of fairness and accuracy ratings in individual sanctioning decisions. Table A-14 presents the full data, including both the average of the two issue areas and the results for each issue—criminal sentencing and restraining orders—separately.

[19]The strong disapproval is also evident in the between-subject experiment. As tables A-4 shows, the percentage of respondents who found the use of ADS in this context to be appropriate is significantly low,

the question format explicitly asked respondents to compare these dimensions, potentially incentivizing them to identify differences.[20]

The remaining two decision types—assisting individuals and sanctioning collectives—elicit more ambivalent opinions, with respondents grappling with trade-offs between fairness and accuracy, consistent with theoretical predictions. For decisions assisting individuals (e.g., determining eligibility for food stamps or study assistance), the perceived fairness of using ADS is significantly higher than its perceived accuracy ($p<0.05$ and $p<0.001$, respectively). Conversely, for decisions sanctioning collectives (e.g., increasing enforcement for illegal construction or work), perceived accuracy significantly outweighs perceived fairness ($p<0.001$). This aligns with the theory, which suggests that while ADS may improve accuracy in such contexts due to their ability to process vast amounts of data, using them to sanction rather than assist targeted communities can be seen as unfair.

The between-subjects analysis further supports these findings. Figure A-3 illustrates the predicted appropriateness, fairness, and accuracy of ADS for each decision type, based on a mixed-effects model that regresses these outcomes on indicators for the decision-type treatments using random intercepts for the policy domain and the respondent. Notably, when ADS are used to sanction collectives, a significant difference emerges: while perceived accuracy is higher, respondents find this use significantly less appropriate. The confidence intervals reveal a significant gap between perceived accuracy and appropriateness, whereas perceptions of appropriateness and fairness do not significantly differ. This pattern aligns with the theoretical expectation that even if perceived to improve accuracy, ADS are less tolerated for decisions involving sanctions given their high-stake consequences which are less reversible compared to other types of policy decisions. The result is also consistent with

ranging from 15 (child welfare and education) to no more than 20 (in policing).

[20] One potential concern is that the results may reflect people's general aversion towards these decisions, regardless of the decision-maker. The Policy Evaluation experiment addresses this concern by isolating the effect of the decision-maker (human vs. algorithm) on policy support.

previous work showing that the public prior values of fairness when contemplating the use of ADS in government (Schiff, Schiff, and Pierson, 2021).[21]

Policy Evaluation Experiment

The results of so far reveal systematic variation in citizens' willingness to accept ADS across contexts depending on the type of the decision at stake. When asked directly, people particularly oppose using AI-based tools in decisions that sanction individuals but are more willing to accept such uses as appropriate to inform decisions about assistance, especially for collectives.

What are the political implications of these views? Do they actually shape policy outcomes in practice? To address this question, I conducted a second experiment in which respondents were randomly assigned to evaluate identical policy proposals that differed only in the identity of the decision-maker implementing them. By holding policy content constant and varying only the decision-maker, I can assess whether citizens' views on ADS influence their support for the policies these systems inform. By examining whether people assess the same policies differently based solely on who implements them, the experiment sheds light on the potential consequences of integrating ADS for the perceived legitimacy of policy actions.

Specifically, all respondents were asked to evaluate four policy proposals presented in random order: (1) prioritizing housing based on disability rather than waiting period; (2) investigating allegations based on the risk of child abuse instead of investigating all allegations; (3) allocating police patrols based on the risk of crime rather than allocating patrols at random; and (4) providing extra funding for alcohol and drug education programs for selected

[21] It is important to note that while this analysis provides suggestive evidence in line with the patterns predicted by the theory, it does not estimate the relative effects of accuracy and fairness on the assessment of ADS appropriateness. This is because the design treats them as three dependent variable outcomes. Experimentally isolating these two considerations will be an important task for future research.

schools identified as problematic. The wording of each policy proposal and the treatment conditions are presented in Table 3. These four scenarios were chosen according to two distinguishing features derived from the theory, and were based on real-world initiatives of using ADS that are currently being promoted or implemented in the public sector.[22]

For each policy proposal, I independently randomized the identity of the decision-maker implementing the policy decisions while holding the policy content constant: a human officer in the control group and a predictive algorithm in the treatment group.[23] While the theoretical focus is on comparing ADS to traditional human decision-makers, many real-world applications involve hybrid use in which the algorithm assists, rather than fully replaces, human decision-makers. To reflect these practices, the experiment also includes a third condition, where a human decision-maker is assisted by an algorithmic system. The full results are reported in the Appendix C.3.1 and will be discussed later in more detail.

The key dependent variable measures support for the policy proposal. Respondents were asked to indicate the degree to which they support or oppose a policy proposal, with answers on a five-point scale ranging from "strongly oppose" to "strongly support." As preregistered, to facilitate the interpretation of the results, I re-coded the scale to a binary measure with a value of 1 for positive answers ("strongly support" or "somewhat support") and 0 otherwise.[24]

A central feature of the experiment's design was to focus respondents on the policy itself rather than the identity of the decision-maker. For instance, in the housing proposal, respondents were asked whether they supported prioritizing public housing based on disability rather than time spent on the waiting list; the entity assessing disability—whether a human

[22]The experiment employed detailed vignettes to enhance realism and clarify the specific policy dilemmas at stake. However, these longer vignettes imposed a greater cognitive burden on respondents. This, combined with constraints based on power calculations, limited the number of scenarios that could be presented and randomized to four in total, each representing a distinct decision type and drawn from a different policy domain with real-world implications for legitimacy. Future research should aim to replicate these findings using a broader range of other scenarios

[23]Summary statistics, and balance tests across experimental conditions are reported in Table A-15.

[24]Using this binary outcome allows me to capture the potential shifts in respondents who were initially indifferent about the policy—this is a key segment that could determine political outcomes.

Table (3) Policy scenarios and experimental treatments

	Individuals	Collectives
Assisting	***Public Housing*** **The issue:** Homelessness has increased over the past decade. The number of people currently homeless exceeds the number of affordable housing units available to them. **Policy solution:** To manage this shortage, some propose that [treatment condition] should decide which individuals receive housing first, prioritizing those with the most severe disabilities for assistance, regardless of the time they have been waiting on the list.	***Public Education*** **The issue:** In recent years, violent crime among juveniles has increased nationwide. Many of these crimes have been committed under the influence of drugs and alcohol. **Policy solution:** To address this problem, some propose that [treatment condition] should decide which schools receive additional funding for alcohol and drug education programs based on an assessment of the risk of juvenile crime in the area.
Sanctioning	***Child Welfare*** **The issue:** The number of calls reporting suspected child abuse or neglect is very high. Yet, some of them turn out to be false. **Policy solution**: To manage the high number of reports, some propose that instead of investigating every allegation, [treatment condition] should decide which allegation to investigate based on a preliminary assessment of the family's risk of child abuse or neglect.	***Policing*** **The issue**: As part of the fight against rising crime in the U.S., many police departments are concentrating their efforts on preventing incidents from occurring by increasing deterrence, instead of reacting to incidents after they occur. **Policy solution**: As part of this approach, some propose that instead of random patrols, [treatment condition] should decide where police officers patrol based on a prediction of where crimes are most likely to occur.

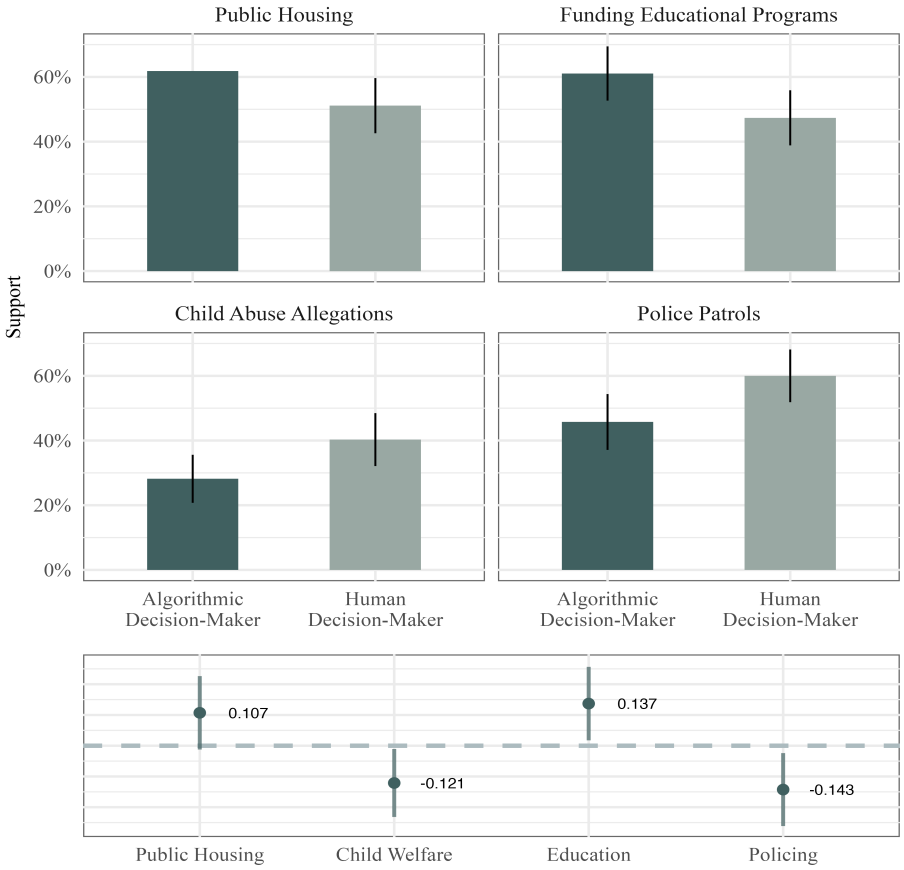
Notes: This table provides the wording of the policy scenarios and the experimental conditions. The full text of all questions in the survey is available in the Appendix.

officer or an algorithm—was not the focus of the question. This was crucial because introducing algorithmic decision-making could itself be perceived as a policy reform, potentially leading to systematic differences in how the control and treatment groups interpret the question and biasing the results. By focusing on the core policy dilemma, the design allows for a cleaner assessment of whether citizens implicitly consider the use of ADS when evaluating policies in realistic settings.

Results: Effect of decision-maker on policy support

Do ADS affect public support for policy decisions? I estimate the average treatment effects of the decision-maker treatment on support for the four policy proposals. To identify the initial reactions and avoid spillover effects, in which respondents evaluate the subsequent policy proposals compared to the decision makers presented in the previous scenario, the primary analysis is based only on data collected from the first scenario that was presented to participants. This means that the analysis is based on a between-subjects design in which both the identity of the decision maker and the policy area were varied in a random fashion.

Figure (5) Average policy support, by decision-maker and context



Notes: The figure shows average support for each proposal as a function of the decision-maker condition. The sample includes responses to the first scenario. Error bars indicate 95% CI. The bottom panel shows the results of LPMs, without controls, studying the effect of an ADS on the likelihood of supporting each proposal. Thick bars represent 90% CI; thin bars represent 95% CI. The full results, reported in A-16 based on responses collected from the first scenario.

Table A-18 replicates the analysis with data from all scenarios, controlling for the order of the scenarios. The results remain in the same direction, but the magnitude of effects is somewhat weaker.

Figure 5 shows the percentage of respondents who support each policy proposal as a function of the decision-maker treatment: human versus algorithmic. Consistent with the theoretical expectations, the results show that people do not respond uniformly to the use of ADS in public policy. Respondents who were presented with an algorithmic decision-maker

were, on average, 14 percentage points less likely to support the proposal to allocate police forces to patrol than those who were presented with a human decision-maker (p<0.05). This effect is both statistically and substantively significant, decreasing support from 60% to less than 46%. The bottom panel of Figure 5 shows a similar negative effect in the context of child welfare– involved decisions designed to sanction individuals rather than collectives. Respondents were 12 percentage points less likely to support the proposal for choosing which child abuse allegation to investigate when an algorithm assesses the risk of child abuse or neglect in the family (p<0.05).

In the other two proposals that involved assisting rather than sanctioning decisions– prioritizing public housing and allocating funds to education programs–we see very different trends. The results show that respondents were almost indifferent to ADS in the context of assisting individuals. If anything, using a predictive algorithm instead of public housing officials increases the probability of supporting the proposal to prioritize housing based on disability rather than the time spent on the waiting list.

I find even stronger treatment effects in the context of assisting collectives with regard to the proposal to choose specific schools to receive funding for drug and alcohol education programs. The percentage of citizens expressing at least some support for this policy significantly increases by almost 14 percentage points when a predictive algorithm, rather than members of the school board, assesses the risk of juvenile crime in the area (p<0.05). To get a better sense of the substantive size of this effect, Table A-18 reports the effect of ADS on support for the policy, adjusting for sociodemographic factors. The table shows that the treatment effect is equal to the partisan difference in policy support between Democrats and Republicans.[25]

I also assess the possibility that using algorithmic systems to assist rather than replace human decision-makers might have a different effect on public support. Table A-17 estimates

[25]Table A-19 results are of a similar magnitude when using the alternative outcome measures.

the average treatment effect (ATE) while comparing the ADS and the hybrid conditions, showing little difference between these two conditions across policy domains. The sole exception I find to this pattern is policing. Interestingly, while the use of a predictive algorithm alone has a significant negative effect on support relative to the human decision-maker condition, support for this policy significantly increases when the predictive algorithm is used as a support tool (p<0.01). This is consistent with evidence of a trade-off that people face in using ADS in decisions that sanction collectives, which are considered less fair but relatively accurate. It seems that in decisions of this type, using algorithms as a supportive tool, while keeping the "humans in the loop," appears to be an attractive solution, as it provides more accurate assessments, without sacrificing the human element that is important in decisions with irreversible consequences.

Finally, to test whether the decision context moderates the effect of ADS, Table A-20 in the Appendix examines the interaction effects of ADS and the policy proposal (presented first to the respondent) on the probability of supporting the policy. The effect of ADS is negative and significant, suggesting that overall, respondents are less likely to support policies implemented by ADS. However, the negative effect of the decision maker is offset and even reversed in policy proposals involving decisions about assisting collectives.[26]

Overall, the results from the two experiments together provide support for the theory, suggesting that people are particularly sensitive to human presence in sanctioning decisions, which have less reversible consequences for the lives of either individuals or collectives.

[26]A potential concern is that the variation in policy support observed across the four scenarios might stem from differences in policy domains rather than from the decision type. However, the primary goal of this experiment was not to systematically isolate the effect of decision type—a task addressed by the Decision Type Experiment. Instead, this experiment assesses the practical implications of public attitudes toward ADS for policy legitimacy in high stake cases. Thus, the findings regarding variation across decision types are suggestive, and should be interpreted in light of the evidence from the Decision Type Experiment. Furthermore, as shown in Appendix Table A-9, when controlling for decision type, when controlling for decision type, differences between policy domains are minimal and not statistically significant. The coefficient comparing public education to child welfare (the reference domain) is -0.010 (0.013), indicating that, if anything, respondents were slightly less likely to accept algorithmic decision-making in education compared to child welfare contexts, though this difference was not statistically significant at any level.

Adopting ADS in these contexts can significantly reduce the overall support for the policy decisions and actions they implement.[27]

Conclusion and Implications

This article puts forward a theoretical framework and leverages a set of survey experiments to explain public attitudes and preferences on the use of ADS in governance. Moving beyond examining attitudes at the policy domain level, the theory calls for distinguishing between four types of decisions when contemplating ADS uses. The experimental results provide strong support for this theory. Using evidence from a broad range of policy domains and issues, I show that citizens resist the use of ADS in decisions that sanction, especially individuals, but are more willing to accept the use of these systems in decisions that assist, especially collectives. Returning to the California referendum example, the analysis suggests that the public rejection of replacing cash bail with a risk assessment algorithm reflects citizens' sensitivity to the specific use of ADS in sanctioning decisions that have less reversible consequences for individuals' lives. Algorithms in these contexts are perceived as both less fair and less accurate compared to human decision-makers.

Together, the theory and findings have important implications for directing industry and government efforts to govern AI development and implementation responsibly. The study provides a more granular framework that helps identify ex-ante where AI-based tools will be deemed appropriate and where they might trigger a backlash. To date, much of the effort to govern AI pays little attention to public opinion—those who ultimately bear the consequences of AI-based decisions without the choice to opt-out. Yet, as this study shows, even if engineers and ethicists agree on the proper use of AI, these solutions will not be

[27] Citizens' aversion to ADS in sanctioning decisions may reflect patterns of loss aversion, where potential losses (e.g., restrictions of rights) loom larger than equivalent gains (e.g., access to resources). This psychological mechanism could help explain heightened sensitivity to algorithmic decisions with less reversible consequences. Testing this and other potential psychological mechanisms empirically represents an important direction for future research.

politically feasible if they are not accepted by the public. The analysis reveals that public support for decisions designed to sanction individuals fell significantly when made by an algorithm rather than by a human decision-maker. The implications of this are already being seen in recent high-profile cases of governments and municipalities backtracking or canceling initiatives that used ADS due to public outcry (e.g., Austen and Wakabayashi, 2020; Weale and Stewart, 2020).

Specifically, the finding that the same algorithmic systems can be accepted as legitimate in certain decisions but rejected in others theoretically predictable contexts, underscores the limitations of recent efforts to articulate a universal prescription for a fair and accurate algorithmic system. The analysis indicates that design efforts and implementation strategies may benefit from being tailored to different contexts in ways that consider citizens' concerns.

Furthermore, the study provides insight into the feasibility of hybrid solutions that integrate human input and algorithmic assessment. This option is particularly attractive in decisions that sanction collectives, where algorithmic accuracy advantages can be leveraged while maintaining human oversight for fairness considerations. This finding highlights the need for future research to examine more precisely how different configurations of human-algorithm collaboration affect public trust and perceived legitimacy across contexts.

This study adopted a broad definition of ADS, focusing on predictive software that relies on extensive data to make decisions without direct human instruction. This simplification aligns with current public understanding of AI-based algorithms and allows for a clear focus on the contextual factors influencing public attitudes. However, the algorithmic systems used in the public sector vary significantly in design and technical features, such as the size and source of training data and the number of factors considered. This raises the question of how these technical features interact with contextual factors. For example, while previous research suggests that people perceive algorithms trained on larger datasets as more reliable (Waggoner et al., 2019), the findings indicate this may not hold true for all types of decisions.

In decisions involving sanctions on individuals, technical features ensuring accountability may be prioritized over data size. Therefore, further research is needed to explore the interplay between ADS technical features and the specific contexts in which they are used.

Moreover, variation in public views across contexts is more nuanced than the 2-by-2 framework introduced in this paper. The two dimensions are not all-encompassing, but they provide a useful starting point for further investigation of other relevant contextual factors shaping public preference for using ADS. For example, while this study focuses on whether the algorithmic decision targets individuals or collective cases, another factor that might be relevant is the way the target population is perceived-—whether they are seen as deserving or undeserving of assistance or perceived as threatening or non-threatening when it comes to sanctioning decisions (Schneider and Ingram, 1993).

Finally, this study documented mass preferences at a relatively early stage of public debate, at a time when most citizens are just becoming aware of ADS and their increasing role in informing high-stakes decisions. As the use of algorithmic tools in government continues to grow, more stakeholders - including technology companies, politicians, and civil society organizations - will seek to inform the public about the potential impact of this technology. Whether and how citizens' views shift in response to new information and the extent to which they rely on cues from elite actors is a promising avenue for future study to understand the evolving politics of using AI and data-driven algorithms in government.

Overall, as this study makes clear, the growing integration of AI-based tools in governance touches on the very core of democracy—how we make public decisions. As such, it raises questions regarding the legitimacy and accountability of these decisions, inspiring a research agenda in political science on the political repercussions of this major technological change.

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Online Appendix for:
"When Do Citizens Resist The Use of AI Algorithms in Public Policy
Theory and Evidence"

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A Data Description

A.1 Descriptive Statistics

As mentioned in the main text, I conducted two original experiments embedded in a national U.S. survey, using samples of 1,590 adults collected by Dynata an Internet survey company (formerly Survey Sampling International - SSI). I imposed quotas on gender, age, education, and race/ethnicity. Table A-1 reports the characteristics of the sample compared with those of the overall US population. Data come from the 2020 U.S. Census Bureau. As the table shows, the sample is representative along the quota dimensions.

Table (A-1) Summary statistics for the survey sample

Quotas	Population Percent	Sample N	Sample Percent
	Age		
18-24	13.0	206	13.0
25-34	19.0	295	18.6
35-44	22.0	357	22.6
45-54	18.0	271	17.1
55+	28.0	453	28.6
	Race		
White	60.7	976	61.7
Hispanic	18.1	252	15.9
Black	13.4	219	13.8
Asian	7.8	90	5.7
	Gender		
Male	48.0	761	48.1
Female	52.0	821	51.9
	Education		
Some College or Less	61.7	949	60.0
Associate's Degree or Higher	38.3	633	40.0

A.2 Survey Questionnaire

This section gives the exact wording of the policy scenarios, the experimental conditions, and the survey questions included in the survey. As mentioned, to minimize the potential concern of social desirability, respondents were not informed about the study's focus on using ADSs. Instead, they were asked about their views on four policy proposals.

Definitions: Before beginning, please read these definitions that are relevant to the policies: (1) The pretrial stage in the criminal justice system is the time between arrest and trial. (2) A predictive algorithm is computer software that makes decisions without human instruction, relying on a massive amount of data. (3) Homelessness is defined as living somewhere that is below a minimum quality standard or that you can be evicted from with little or no warning.

Attention check 1 (screener): On the previous page, you were presented with three definitions that are relevant to the policies. Please select the definition that did not appear among the previous three definitions: (4) Screeners are workers in child welfare who respond to the hotline calls reporting child abuse allegations.

Attention check 2 (screener): People are very busy these days and many do not have time to follow what goes on in the government. We are testing whether people read questions. To show that you've read this much, answer both extremely interested and very interested.

Outcome questions: Decision-Type experiment)
Perceived Appropriateness: Next, we ask that you read the descriptions of several policy decisions. For each, please indicate how appropriate it is to have that decision made by an algorithm rather than by a human being. Extremely appropriate 1 to Extremely inappropriate 7.

Perceived Accuracy and Fairness: People think differently about the extent to which algorithms would be accurate compared to fair. In some decisions, an algorithm may be considered accurate but unfair; in other decisions fair but inaccurate; and in some other decisions unfair and inaccurate; or both fair and accurate. For the same decisions you have just evaluated. Please indicate how FAIR/ACCURATE and ACCURATE/FAIR you think an algorithm would be in...

Technological Literacy: How familiar are you with the following computer and Internet-related items? Please choose a number between 1 and 5 where 1 represents "Totally unfamiliar," and 5 represents "Very familiar". Phishing; Cache; PDF; Tagging; JPEG; Malware; RSS; HTTP cookie; Fitibly.

Figures A-1 and A-2 provide a screenshot of the matrix presented to the respondent in the decision-type experiment.

A.3 Decision-Type Experiment: Treatment Wording

Table 2 in the main text details the wording of the treatment conditions randomized in the first (between-subjects) component of the decision-type experiment: four types of decisions within each of three policy domains—policing, child welfare, and education. Table A-2 below details the treatment conditions randomized in the second (within-subjects) component: two different issue areas for each of the four decision types.

B Decision-Type Experiment

B.1 Descriptive Statistics

Table A-5 below presents descriptive statistics for the main dependent variables: the perceived appropriateness, fairness, and accuracy of using algorithmic decision systems (ADS)

Figure (A-1) Screenshot of the Decision-Type Experiment: Perceived Appropriateness

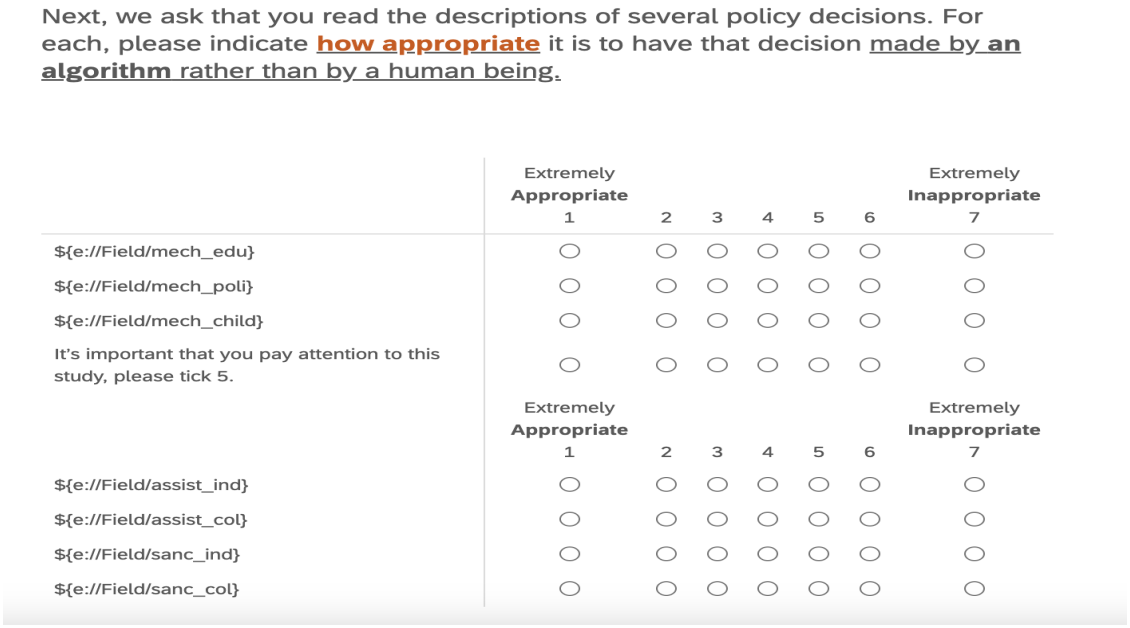


Figure (A-2) Screenshot of the Decision-Type Experiment: Perceived Accuracy vs. Fairness

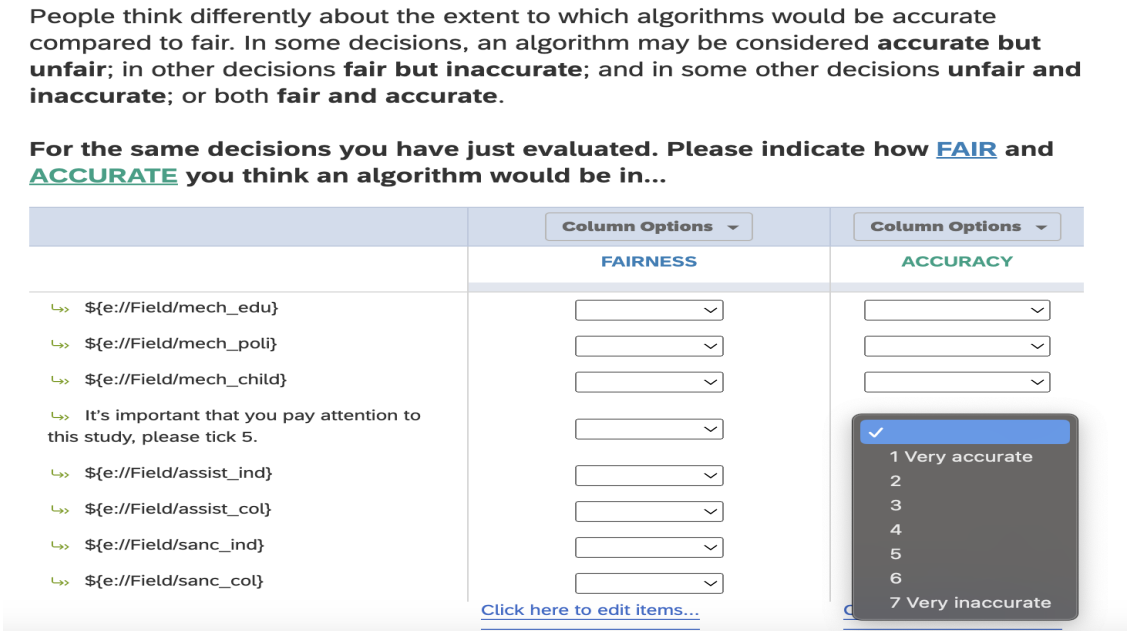


Table (A-2) Decision Wordings Randomized in the Within-Subjects Component

	Decisions
Assisting individuals	Deciding which individual should receive food stamps based on an assessment of the neediness of the requester. Deciding which pupils should be offered study assistance based on an assessment of early learning problems in school.
Assisting collectives	Deciding where to build shelters for homeless people based on an assessment of the risk of homelessness in the area. Deciding where to place fire stations based on a prediction of the risk of fire outbreaks nearby.
Sanctioning individuals	Determining a sentence based on an assessment of the defendant's risk of committing another crime. Determining whether a restraining order should be issued based on a prediction of the individual's risk of assaulting their intimate partner.
Sanctioning collectives	Deciding where to increase police enforcement based on an assessment of the likelihood of illegal work in the area. Deciding where to increase police enforcement based on an assessment of the likelihood of illegal building in the area.

Notes: This table details the treatment conditions included in the within-subject experiment. All respondents were presented with the four types of decisions, where the manipulation is in the issue area.

across the three policy domains, by the four types of decisions randomly assigned to respondents.

B.2 Decision-Type Experiment: Between-Subjects Component Results

This section provides the demographic balance tables for the between-subjects experiment. The tables below show the results of t-tests of each treatment condition for each policy domain. Results confirm that the randomization of treatment assignment makes the four groups essentially identical to one another on average.

B.3 Between-Subjects Results

Table A-6 below reports estimates from linear probability models studying the effect of (1) the subject of the decision and (2) its objective on the probability of viewing the use of ADS as appropriate across three policy areas: education, policing, and child welfare. The analysis limits the sample to responses to the first item, which provides the cleanest comparison. In the first model for each policy area (columns 1, 4, and 7), reports minimal specifications. The second model for each area (columns 2, 5, and 8) includes demographic controls: age, gender, political identification, education level, race, and digital literacy. The third model for each area (columns 3, 6, and 9) replaces digital literacy with prior knowledge of AI. This measure captures respondents' familiarity with the increasing use of algorithmic systems in public decision-making, aligning more closely with the knowledge domain relevant to this research.

Table (A-3) Summary of statistics of Perceived Accuracy, Fairness, and Appropriateness

Consideration	Context	Type	Mean	n	SD	SE
Appropriateness	Education	Assisting Collectives	3.66	397	2.16	0.11
		Assisting Individuals	3.51	396	2.10	0.11
		Sanctioning Collectives	3.51	391	2.13	0.11
		Sanctioning Individuals	2.78	398	1.82	0.09
	Policing	Assisting Collectives	4.48	386	2.20	0.11
		Assisting Individuals	2.90	399	1.89	0.09
		Sanctioning Collectives	3.64	403	2.12	0.11
		Sanctioning Individuals	2.97	394	1.92	0.10
	Child Welfare	Assisting Collectives	0.48	397	0.50	0.03
		Assisting Individuals	0.35	395	0.48	0.02
		Sanctioning Collectives	0.30	401	0.46	0.02
		Sanctioning Individuals	0.18	389	0.38	0.02
Fairness	Education	Assisting Collectives	4.37	397	1.85	0.09
		Assisting Individuals	4.12	396	1.95	0.10
		Sanctioning Collectives	3.96	391	1.91	0.10
		Sanctioning Individuals	3.25	398	1.76	0.09
	Policing	Assisting Collectives	4.87	386	1.80	0.09
		Assisting Individuals	3.57	399	1.84	0.09
		Sanctioning Collectives	4.28	403	1.84	0.09
		Sanctioning Individuals	3.49	394	1.91	0.10
	Child Welfare	Assisting Collectives	4.38	397	1.83	0.09
		Assisting Individuals	3.79	395	1.84	0.09
		Sanctioning Collectives	3.89	401	1.73	0.09
		Sanctioning Individuals	3.15	389	1.91	0.10
Accuracy	Education	Assisting Collectives	4.51	397	1.81	0.09
		Assisting Individuals	4.15	396	1.78	0.09
		Sanctioning Collectives	4.53	391	1.70	0.09
		Sanctioning Individuals	3.86	398	1.78	0.09
	Policing	Assisting Collectives	4.89	386	1.73	0.09
		Assisting Individuals	3.45	399	1.80	0.09
		Sanctioning Collectives	4.62	403	1.74	0.09
		Sanctioning Individuals	3.76	394	1.86	0.09
	Child Welfare	Assisting Collectives	4.32	397	1.79	0.09
		Assisting Individuals	3.66	395	1.77	0.09
		Sanctioning Collectives	4.08	401	1.68	0.08
		Sanctioning Individuals	3.26	389	1.87	0.09

Table (A-4) Summary of statistics of binary outcomes

Decision Type	Policy Domain	Consideration		
		Appropriateness	**Fairness**	**Accuracy**
Sanction Individuals	Education	0.166 (0.018)	0.234 (0.021)	0.367 (0.024)
	Child welfare	0.177 (0.019)	0.247 (0.021)	0.247 (0.021)
	Policing	0.218 (0.020)	0.289 (0.022)	0.340 (0.023)
Assist Individuals	Policing	0.246 (0.021)	0.333 (0.023)	0.288 (0.022)
	Child welfare	0.347 (0.024)	0.387 (0.024)	0.291 (0.022)
	Education	0.384 (0.024)	0.447 (0.025)	0.409 (0.024)
Sanction Collectives	Child welfare	0.302 (0.023)	0.362 (0.024)	0.406 (0.024)
	Education	0.335 (0.023)	0.373 (0.024)	0.527 (0.025)
	Policing	0.367 (0.024)	0.444 (0.024)	0.558 (0.024)
Assist Collectives	Education	0.378 (0.024)	0.474 (0.025)	0.509 (0.025)
	Child welfare	0.479 (0.025)	0.496 (0.025)	0.491 (0.025)
	Policing	0.560 (0.025)	0.598 (0.025)	0.593 (0.025)

Table A-7 presents two key robustness checks for the main findings. First, it shows that the results remain robust when analyzing the full sample while controlling for the order in which the three policy domains (education, policing, and child welfare) were presented to respondents. Second, it demonstrates that the findings are consistent across alternative measures of the outcome variable. Columns 1-3 use the original binary coding (top three categories of appropriateness), columns 4-6 use a more conservative binary coding (top two categories only), and columns 7-9 use the full seven-point appropriateness scale. Across all specifications, the main effects remain stable and statistically significant. Notably, the order variable is not statistically significant across all models, suggesting that the sequence of presentation did not influence respondents' evaluations.

Table A-8 below presents robustness checks of the main findings, demonstrating consistent results when controlling for respondent attentiveness. Two measures of attentiveness are employed: (1) whether respondents passed an attention check embedded within the decision-type experiment matrix (Models 2, 5, 8), and (2) response time per question, accounting for both those who rushed through the survey and those who may have been distracted (Models 1, 4, 7). Models 3, 6, and 9 replicate the results using logistic regression instead of LPMs for further robustness.

Table A-9 replicates the results using mixed-effects linear regressions. I estimate three separate models for alternative measures of the outcomes: Model 1 estimates the treatment effects on the main outcome of perceived appropriateness using the top three categories on the 7-point scale; As preregistered, I replicate the results, using the following alternative measures of the outcome variables: (1) a binary measure with a value of 1 for the last three options indicating "appropriate" and 0 otherwise (see Model 2); (2) continuous outcomes of a seven-point scale, with higher values indicating very appropriate (Model 3). The results are very much consistent with the main findings.

Table (A-5) Balance tests

Domain	Characteristic	Assisting Collectives	Assisting Individuals	Sanctioning Collectives	Sanctioning Individuals	p-value
Policing Domain						
	N	118	126	140	151	
	Gender (%)					0.594
	Male	59 (50.0)	69 (54.8)	79 (56.4)	75 (49.7)	
	Female	59 (50.0)	57 (45.2)	61 (43.6)	76 (50.3)	
	Age (%)					0.326
	18–24	11 (9.3)	13 (10.3)	22 (15.7)	15 (9.9)	
	25–34	25 (21.2)	23 (18.3)	22 (15.7)	36 (23.8)	
	35–44	25 (21.2)	30 (23.8)	32 (22.9)	29 (19.2)	
	45–54	24 (20.3)	22 (17.5)	32 (22.9)	25 (16.6)	
	55–64	7 (5.9)	18 (14.3)	12 (8.6)	21 (13.9)	
	65+	26 (22.0)	20 (15.9)	20 (14.3)	25 (16.6)	
	Education (%)					0.985
	Associate's Degree or Higher	48 (40.7)	52 (41.3)	56 (40.0)	59 (39.1)	
	Some College or Less	70 (59.3)	74 (58.7)	84 (60.0)	92 (60.9)	
	Race (%)					0.499
	Non-White	41 (34.7)	53 (42.1)	61 (43.6)	63 (41.7)	
	White	77 (65.3)	73 (57.9)	79 (56.4)	88 (58.3)	
	Digital Literacy (%)					0.455
	Low Digital Literacy	72 (61.0)	83 (65.9)	81 (57.9)	99 (65.6)	
	High Digital Literacy	46 (39.0)	43 (34.1)	59 (42.1)	52 (34.4)	
Education Domain						
	N	123	137	124	124	
	Gender (%)					0.136
	Male	59 (48.0)	58 (42.3)	48 (38.7)	65 (52.4)	
	Female	64 (52.0)	79 (57.7)	76 (61.3)	59 (47.6)	
	Age (%)					0.847
	18–24	16 (13.0)	20 (14.6)	21 (16.9)	20 (16.1)	
	25–34	25 (20.3)	23 (16.8)	21 (16.9)	23 (18.5)	
	35–44	24 (19.5)	29 (21.2)	30 (24.2)	23 (18.5)	
	45–54	19 (15.4)	19 (13.9)	19 (15.3)	24 (19.4)	
	55–64	10 (8.1)	19 (13.9)	16 (12.9)	12 (9.7)	
	65+	29 (23.6)	27 (19.7)	17 (13.7)	22 (17.7)	
	Education (%)					0.523
	Associate's Degree or Higher	48 (39.0)	56 (40.9)	40 (32.3)	47 (37.9)	
	Some College or Less	75 (61.0)	81 (59.1)	84 (67.7)	77 (62.1)	
	Race (%)					0.975
	Non-White	45 (36.6)	47 (34.3)	43 (34.7)	45 (36.3)	
	White	78 (63.4)	90 (65.7)	81 (65.3)	79 (63.7)	
	Digital Literacy (%)					0.764
	Low Digital Literacy	88 (71.5)	91 (66.4)	86 (69.4)	82 (66.1)	
	High Digital Literacy	35 (28.5)	46 (33.6)	38 (30.6)	42 (33.9)	
Child Welfare Domain						
	N	129	143	138	129	
	Gender (%)					0.988
	Male	60 (46.5)	66 (46.2)	65 (47.1)	58 (45.0)	
	Female	69 (53.5)	77 (53.8)	73 (52.9)	71 (55.0)	
	Age (%)					0.381
	18–24	16 (12.4)	27 (18.9)	16 (11.6)	9 (7.0)	
	25–34	27 (20.9)	26 (18.2)	23 (16.7)	21 (16.3)	
	35–44	28 (21.7)	32 (22.4)	36 (26.1)	39 (30.2)	
	45–54	20 (15.5)	17 (11.9)	27 (19.6)	23 (17.8)	
	55–64	16 (12.4)	14 (9.8)	16 (11.6)	12 (9.3)	
	65+	22 (17.1)	27 (18.9)	20 (14.5)	25 (19.4)	
	Education (%)					0.502
	Associate's Degree or Higher	49 (38.0)	59 (41.3)	65 (47.1)	54 (41.9)	
	Some College or Less	80 (62.0)	84 (58.7)	73 (52.9)	75 (58.1)	
	Race (%)					0.982
	Non-White	51 (39.5)	56 (39.2)	53 (38.4)	48 (37.2)	
	White	78 (60.5)	87 (60.8)	85 (61.6)	81 (62.8)	
	Digital Literacy (%)					0.500
	Low Digital Literacy	85 (65.9)	88 (61.5)	84 (60.9)	73 (56.6)	
	High Digital Literacy	44 (34.1)	55 (38.5)	54 (39.1)	56 (43.4)	

Table (A-6) Decision type and perceived appropriateness, by policy domain

	Dependent variable:								
	Education			Policing			Child welfare		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Assisting	0.139^{***}	0.138^{***}	0.142^{***}	0.114^{**}	0.103^{**}	0.095^{*}	0.188^{***}	0.187^{***}	0.182^{***}
	(0.040)	(0.040)	(0.039)	(0.039)	(0.038)	(0.037)	(0.039)	(0.038)	(0.038)
Individuals	-0.099^{*}	-0.095^{*}	-0.104^{**}	-0.279^{***}	-0.280^{***}	-0.272^{***}	-0.099^{*}	-0.095^{*}	-0.096^{*}
	(0.040)	(0.040)	(0.039)	(0.039)	(0.038)	(0.037)	(0.039)	(0.038)	(0.038)
Age		−0.006	−0.007		−0.001	−0.007		0.004	0.002
		(0.013)	(0.013)		(0.013)	(0.013)		(0.013)	(0.013)
Female		−0.022	−0.032		−0.040	−0.054		0.007	−0.013
		(0.040)	(0.040)		(0.038)	(0.038)		(0.038)	(0.038)
Some college or less		−0.012	−0.013		−0.018	−0.022		−0.042	−0.034
		(0.043)	(0.042)		(0.040)	(0.039)		(0.041)	(0.040)
White		0.060	−0.017		0.226^{***}	0.154^{***}		0.114^{**}	0.025
		(0.045)	(0.048)		(0.043)	(0.046)		(0.043)	(0.048)
High tech literacy		-0.114^{*}			-0.107^{**}			-0.098^{*}	
		(0.045)			(0.041)			(0.042)	
Prior Knowledge			-0.263^{***}			-0.236^{***}			-0.247^{***}
			(0.055)			(0.051)			(0.053)
Constant	0.271^{***}	0.307^{***}	0.388^{***}	0.444^{***}	0.389^{***}	0.480^{***}	0.258^{***}	0.231^{**}	0.325^{***}
	(0.035)	(0.079)	(0.079)	(0.034)	(0.074)	(0.076)	(0.033)	(0.077)	(0.078)
Observations	508	508	508	535	535	535	539	539	539
R^2	0.034	0.056	0.086	0.100	0.186	0.207	0.052	0.088	0.116

Notes: This table reports results from LPMs estimated separately for each policy domain. The dependent variable is binary, taking the value of 1 if the respondent deems the use of ADS appropriate in a given policy area and 0 otherwise. The independent variables are indicators for the theoretical dimensions: the target of the decision (assisting or sanctioning) and the object of the decision (individuals or collectives). The reference categories are: collectives and sanctioning. Digital literacy is a binary variable that takes the value 1 if the respondent indicates familiarity with more than 5 items on the matrix of 8 technological-related items. †p<0.1; *p<0.05; **p<0.01; ***p<0.001

Table (A-7) Decision type and appropriateness, full sample controlling for order

	Dependent variable:								
	Education			Policing			Child welfare		
	Binary (3 last cat)	Binary (2 last cat)	7-point scale	Binary (3 last cat)	Binary (2 last cat)	7-point scale	Binary (3 last cat)	Binary (2 last cat)	7-point scale
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Assisting	0.136***	0.068***	0.490***	0.112***	0.081***	0.392***	0.173***	0.106***	0.715***
	(0.023)	(0.020)	(0.097)	(0.022)	(0.020)	(0.094)	(0.022)	(0.020)	(0.094)
Individuals	−0.084***	−0.098***	−0.466***	−0.227***	−0.214***	−1.096***	−0.126***	−0.097***	−0.699***
	(0.023)	(0.020)	(0.097)	(0.022)	(0.020)	(0.094)	(0.022)	(0.020)	(0.094)
Order	0.011	0.001	0.004	−0.018	0.004	−0.056	0.017	0.005	0.075
	(0.014)	(0.012)	(0.059)	(0.014)	(0.012)	(0.058)	(0.014)	(0.012)	(0.058)
Age	−0.011	−0.016*	−0.092**	0.005	0.006	0.010	0.002	−0.004	−0.021
	(0.008)	(0.007)	(0.033)	(0.007)	(0.007)	(0.032)	(0.008)	(0.007)	(0.031)
Female	−0.032	−0.033	−0.099	−0.049*	−0.047*	−0.098	−0.004	−0.004	−0.025
	(0.023)	(0.020)	(0.098)	(0.022)	(0.020)	(0.095)	(0.023)	(0.020)	(0.094)
Some college or less	−0.050*	−0.031	−0.193†	−0.043†	−0.033	−0.219*	−0.027	−0.001	−0.140
	(0.024)	(0.021)	(0.104)	(0.024)	(0.022)	(0.101)	(0.024)	(0.021)	(0.101)
White	0.125***	0.099***	0.981***	0.186***	0.111***	1.129***	0.165***	0.102***	0.936***
	(0.026)	(0.023)	(0.110)	(0.025)	(0.023)	(0.107)	(0.025)	(0.022)	(0.106)
Tech literacy	−0.084***	−0.042†	−0.981***	−0.098***	−0.063**	−0.969***	−0.086***	−0.049*	−1.041***
	(0.025)	(0.022)	(0.108)	(0.025)	(0.022)	(0.105)	(0.025)	(0.022)	(0.104)
Constant	0.307***	0.263***	3.580***	0.394***	0.267***	3.760***	0.207***	0.154***	3.157***
	(0.054)	(0.047)	(0.230)	(0.052)	(0.047)	(0.218)	(0.053)	(0.046)	(0.219)
Observations	1,582	1,582	1,582	1,582	1,582	1,582	1,582	1,582	1,582
R^2	0.060	0.042	0.149	0.140	0.112	0.232	0.103	0.055	0.198

Notes: This table reports results from LPM estimated separately for each policy area for the full sample, controlling for the presentation order of the item in the matrix. †p<0.1; *p<0.05; **p<0.01; ***p<0.001

B.3.1 Fairness vs Accuracy considerations

Figure A-3 plots the predicted values of each of the three outcomes (appropriateness, fairness, accuracy) from the mixed-effects models that regress these binary outcomes on indicators for the decision-type treatments using random intercepts for the policy domain and the respondent. Table A-10 reports the full regression results.

Table (A-8) Decision type and appropriateness, controlling for inattentiveness

	Dependent variable:								
	Education			Policing			Child welfare		
	OLS		*logistic*	*OLS*		*logistic*	*OLS*		*logistic*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Assisting	0.137^{***}	0.137^{***}	0.663^{***}	0.113^{***}	0.113^{***}	0.572^{***}	0.174^{***}	0.172^{***}	0.866^{***}
	(0.023)	(0.023)	(0.113)	(0.022)	(0.022)	(0.115)	(0.022)	(0.022)	(0.115)
Individuals	-0.083^{***}	-0.086^{***}	-0.413^{***}	-0.226^{***}	-0.226^{***}	-1.125^{***}	-0.127^{***}	-0.125^{***}	-0.634^{***}
	(0.023)	(0.023)	(0.112)	(0.022)	(0.022)	(0.117)	(0.022)	(0.022)	(0.114)
Order	0.010	0.011	0.054	−0.018	−0.018	−0.091	0.018	0.018	0.085
	(0.014)	(0.014)	(0.068)	(0.014)	(0.014)	(0.070)	(0.014)	(0.014)	(0.070)
Age	−0.012	−0.011	−0.055	0.004	0.005	0.021	0.002	0.003	0.010
	(0.008)	(0.008)	(0.037)	(0.007)	(0.007)	(0.038)	(0.008)	(0.008)	(0.037)
Female	−0.030	−0.030	−0.165	-0.048^{*}	-0.047^{*}	-0.258^{*}	−0.003	−0.003	−0.026
	(0.023)	(0.023)	(0.113)	(0.022)	(0.022)	(0.115)	(0.023)	(0.023)	(0.114)
Some college or less	$-0.047^{\dagger}$	$-0.043^{\dagger}$	-0.259^{*}	$-0.041^{\dagger}$	−0.038	-0.241^{*}	−0.025	−0.021	−0.146
	(0.024)	(0.024)	(0.120)	(0.024)	(0.024)	(0.123)	(0.024)	(0.024)	(0.122)
White	0.112^{***}	0.114^{***}	0.632^{***}	0.179^{***}	0.179^{***}	0.975^{***}	0.158^{***}	0.157^{***}	0.860^{***}
	(0.026)	(0.026)	(0.130)	(0.026)	(0.025)	(0.135)	(0.026)	(0.026)	(0.134)
Tech literacy	-0.065^{*}	-0.070^{**}	-0.425^{***}	-0.087^{***}	-0.089^{***}	-0.521^{***}	-0.075^{**}	-0.076^{**}	-0.454^{***}
	(0.026)	(0.025)	(0.127)	(0.026)	(0.025)	(0.131)	(0.026)	(0.025)	(0.130)
Inattentive (time)	-0.084^{*}			−0.048			−0.050		
	(0.033)			(0.033)			(0.033)		
Inattentive (matrix)		-0.142^{***}			-0.093^{*}			-0.102^{**}	
		(0.038)			(0.037)			(0.037)	
Constant	0.322^{***}	0.316^{***}	-0.873^{***}	0.403^{***}	0.401^{***}	$-0.502^{\dagger}$	0.215^{***}	0.214^{***}	-1.408^{***}
	(0.054)	(0.054)	(0.265)	(0.052)	(0.052)	(0.266)	(0.053)	(0.052)	(0.269)
Observations	1,582	1,582	1,582	1,582	1,582	1,582	1,582	1,582	1,582
R^2	0.064	0.068		0.141	0.143		0.104	0.107	
Log Likelihood			−936.744			−901.647			−913.383
Akaike Inf. Crit.			1,891.488			1,821.295			1,844.766

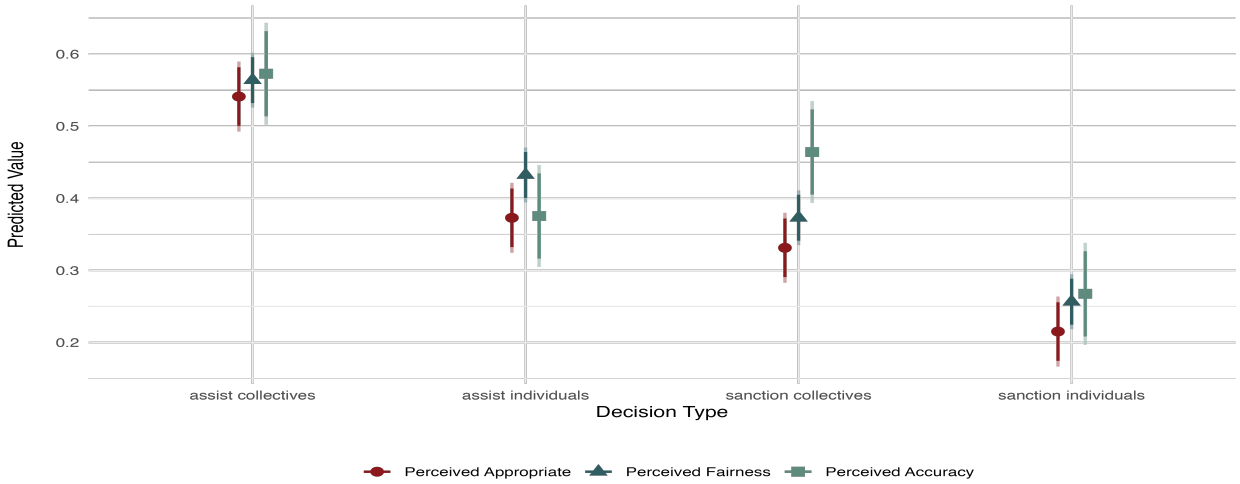
Notes: This table reports results from LPM (models 1-5) or Logistic regression (models 7-9) estimated separately for each policy domain. Models 1, 4, and 7 control for response-time attentiveness, with respondents who completed the survey quickly as the reference category. Models 2, 5, and 8 control for respondents who failed the attention check. †p<0.1; *p<0.05; **p<0.01; ***p<0.001

Table (A-9) Mixed-Effects Linear Regressions for Perceived Appropriateness

	Dependent variable:		
	Perceived appropriate (3 last categories)	Perceived appropriate (2 last categories)	Perceived appropriate (7-point scale)
	(1)	(2)	(3)
Assisting	0.136^{***}	0.078^{***}	0.521^{***}
	(0.012)	(0.010)	(0.045)
Individuals	-0.147^{***}	-0.136^{***}	-0.746^{***}
	(0.012)	(0.010)	(0.045)
Domain: Education	−0.010	0.008	0.022
	(0.013)	(0.011)	(0.048)
Domain: Policing	$0.021^{\dagger}$	0.035^{**}	0.154^{**}
	(0.013)	(0.011)	(0.048)
Age	0.0002	−0.0002	−0.001
	(0.001)	(0.0005)	(0.003)
Female	$-0.029^{\dagger}$	$-0.028^{\dagger}$	−0.075
	(0.017)	(0.015)	(0.078)
Some college or less	-0.037^{*}	−0.019	-0.164^{*}
	(0.018)	(0.016)	(0.083)
White	0.156^{***}	0.103^{***}	1.005^{***}
	(0.019)	(0.017)	(0.088)
Tech Literacy	-0.088^{***}	-0.050^{**}	-0.991^{***}
	(0.019)	(0.017)	(0.086)
Order: second	0.028^{*}	$0.019^{\dagger}$	0.075
	(0.013)	(0.011)	(0.048)
Order: third	0.006	0.006	0.010
	(0.013)	(0.011)	(0.048)
Constant	0.283^{***}	0.207^{***}	3.369^{***}
	(0.038)	(0.033)	(0.167)
Observations	4,746	4,746	4,746
Log Likelihood	−2,682.765	−2,087.068	−9,260.676
Akaike Inf. Crit.	5,393.531	4,202.135	18,549.350
Bayesian Inf. Crit.	5,484.042	4,292.646	18,639.860

Notes: This table presents results from mixed-effects linear regressions analyzing the effect of treatment assignments on the perceived appropriateness of ADS. All models include domain fixed effects (education or policing) and control variables for respondent age, gender, education, race, technology literacy, and question order. Standard errors are clustered at the respondent level. †p<0.1; *p<0.05; **p<0.01; ***p<0.001

Figure (A-3) Decision type and predicted views on ADS, Between Subjects Component



Notes: Each dependent variable takes the value of 1 when a respondent indicates that ADS would be appropriate/fair/accurate in a given context. Thick bars represent 90% confidence intervals; thin bars represent 95% confidence intervals. Thick bars represent 90% confidence intervals; thin bars represent 95% confidence intervals.

Table (A-10) Full results from Figure A-3

	Dependent variable:		
	Perceived Appropriate	Perceived Fair	Perceived accurate
	(1)	(2)	(3)
T2: Assist Individuals	-0.151^{***}	-0.140^{***}	-0.216^{***}
	(0.017)	(0.018)	(0.018)
T3: Sanction Collectives	-0.140^{***}	-0.140^{***}	-0.053^{**}
	(0.017)	(0.018)	(0.018)
T4: Sanction Individuals	-0.283^{***}	-0.269^{***}	-0.231^{***}
	(0.017)	(0.018)	(0.018)
Constant	0.473^{***}	0.528^{***}	0.544^{***}
	(0.016)	(0.018)	(0.033)
Observations	4,746	4,746	4,746
Log Likelihood	−2,727.375	−3,000.481	−2,979.453
Akaike Inf. Crit.	5,468.749	6,014.962	5,972.905
Bayesian Inf. Crit.	5,514.005	6,060.217	6,018.160
Note:			†p<0.1; *p<0.05; **p<0.01; ***p<0.001

B.4 Decision-Type Experiment: Within-Subjects Component

B.4.1 Summary Statistics

Table A-11 presents descriptive statistics for the dependent variables: perceived appropriateness, fairness, and accuracy of using ADS across issue areas randomized within the four types of decisions.

Table (A-11) Summary of statistics of Perceived Accuracy, Fairness, and Appropriateness

Consideration	Decision Type	Issue Area	Mean	n	SD	SE
Appropriateness	Assisting Individuals	Food stamps	3.44	790	2.09	0.07
		Study assistance	3.69	792	2.07	0.07
	Assisting Collectives	Fire stations	4.28	792	2.18	0.08
		Shelters for homeless	4.47	790	2.16	0.08
	Sanctioning Individuals	Restraining order	2.63	780	1.91	0.07
		Sentence	2.97	802	2.01	0.07
	Sanctioning Collectives	Illegal construction	3.39	796	2.02	0.07
		Illegal work	3.58	786	2.03	0.07
Fairness	Assisting Individuals	Food stamps	3.90	790	1.90	0.07
		Study assistance	4.31	792	1.84	0.07
	Assisting Collectives	Fire stations	4.68	792	1.86	0.07
		Shelters for homeless	4.68	790	1.81	0.06
	Sanctioning Individuals	Restraining order	3.13	780	1.88	0.07
		Sentence	3.42	802	1.89	0.07
	Sanctioning Collectives	Illegal construction	3.87	796	1.86	0.07
		Illegal work	4.00	786	1.82	0.07
Accuracy	Assisting Individuals	Food stamps	3.77	790	1.82	0.06
		Study assistance	4.15	792	1.77	0.06
	Assisting Collectives	Fire stations	4.69	792	1.79	0.06
		Shelters for homeless	4.73	790	1.75	0.06
	Sanctioning Individuals	Restraining order	3.19	780	1.80	0.06
		Sentence	3.61	802	1.87	0.07
	Sanctioning Collectives	Illegal construction	4.23	796	1.76	0.06
		Illegal work	4.34	786	1.75	0.06

Table (A-12) Summary of statistics of binary outcomes

Decision Type	Issue Area	Consideration		
		Appropriateness	Fairness	Accuracy
Sanction Individuals	Restraining order	0.177 (0.013)	0.232 (0.015)	0.217 (0.014)
	Criminal Sentencing	0.253 (0.015)	0.281 (0.015)	0.318 (0.016)
Sanction Collectives	Illegal construction	0.312 (0.016)	0.358 (0.017)	0.437 (0.017)
	Illegal work	0.351 (0.017)	0.388 (0.017)	0.491 (0.017)
Assist Individuals	Food stamps	0.335 (0.016)	0.396 (0.017)	0.327 (0.016)
	Study assistance	0.410 (0.017)	0.468 (0.017)	0.424 (0.017)
Assist Collectives	Fire stations	0.527 (0.017)	0.571 (0.017)	0.566 (0.017)
	Homeless Shelters	0.556 (0.017)	0.557 (0.017)	0.580 (0.017)

B.5 Additional results

To ensure the findings are not sensitive to the specific items and decisions used in the between-subject component, I analyze data from the within-subject component. Table A-13 reports results of LPM regressing alternative measures of the main outcome: perceived appropriateness on indicator variables for the two theoretical dimensions—the subject and the objective of the decision—and their interaction while controlling for the issue area randomized for each decision and using fixed effects for respondent. The results are highly consistent with the main findings. Results are of a similar magnitude when using the alternative outcome measure (columns 2-3), and when using linear mixed models (columns 4-6).

Table (A-13) Decision type and appropriateness, controlling for issue area (within-subjects component)

	Dependent variable:					
	Appropriate (3 cat)	Appropriate (2 cat)	Appropriateness (7 cat)	Appropriate (3 cat)	Appropriate (2 cat)	Appropriateness (7 cat)
	OLS	*OLS*	*OLS*	*linear mixed-effects*	*linear mixed-effects*	*linear mixed-effects*
	(1)	(2)	(3)	(4)	(5)	(6)
Individuals	−0.115***	−0.063***	−0.683***	−0.115***	−0.063***	−0.683***
	(0.013)	(0.012)	(0.052)	(0.013)	(0.012)	(0.052)
Assisting	0.210***	0.188***	0.893***	0.210***	0.188***	0.893***
	(0.013)	(0.012)	(0.052)	(0.013)	(0.012)	(0.052)
Issue area: Study assistance	−0.250	0.000	0.000	0.043*	0.018	0.144†
	(0.266)	(0.236)	(1.025)	(0.017)	(0.015)	(0.082)
Issue area: Shelters for homeless	−0.750**	−0.500*	−3.000**	0.010	0.003	0.063
	(0.266)	(0.236)	(1.025)	(0.017)	(0.015)	(0.082)
Issue area: Sentence	0.750**	0.750**	5.250***	0.033*	0.018	0.196*
	(0.266)	(0.236)	(1.025)	(0.017)	(0.015)	(0.082)
Issue area: Illegal work	0.000	0.250	0.250	0.011	0.005	0.076
	(0.376)	(0.333)	(1.449)	(0.017)	(0.015)	(0.082)
Order 2	−0.011	−0.002	0.020	−0.011	−0.002	0.020
	(0.013)	(0.012)	(0.052)	(0.013)	(0.012)	(0.052)
Order 3	0.001	0.001	0.033	0.001	0.001	0.033
	(0.013)	(0.012)	(0.052)	(0.013)	(0.012)	(0.052)
Order 4	−0.028*	−0.021†	−0.068	−0.028*	−0.021†	−0.068
	(0.013)	(0.012)	(0.052)	(0.013)	(0.012)	(0.052)
Individuals X Assisting	−0.053**	−0.106***	−0.128†	−0.053**	−0.106***	−0.128†
	(0.019)	(0.017)	(0.073)	(0.019)	(0.017)	(0.073)
Constant	0.225	−0.280	0.681	0.292***	0.177***	3.245***
	(0.624)	(0.553)	(2.404)	(0.022)	(0.019)	(0.102)
Observations	6,328	6,328	6,328	6,328	6,328	6,328
R^2	0.543	0.529	0.655			
Log Likelihood				−3,733.977	−2,947.396	−12,628.810
Akaike Inf. Crit.				7,493.954	5,920.792	25,283.620
Bayesian Inf. Crit.				7,581.739	6,008.578	25,371.400

Notes: Standard errors are clustered at the respondent level. †p<0.1; *p<0.05; **p<0.01; ***p<0.001

B.5.1 Perceived Fairness and Accuracy

Table A-14 examines potential trade-offs between fairness and accuracy in algorithmic decision-making across different contexts. For each decision type, "Average" represents the mean rat-

ings across both issue areas. The "Fairness" and "Accuracy" columns show the proportion of respondents rating algorithmic decisions as fair/accurate. The p-value is from paired t-tests comparing fairness and accuracy ratings within each decision type/issue area. For example, in "Assist Individuals" decisions, algorithms are perceived as significantly fairer than accurate ($p<0.001$), while in "Sanction Collectives" decisions, they are viewed as significantly more accurate than fair ($p<0.001$). In contrast, there is no significant trade-off for "Assist Collectives" decisions ($p=0.370$).

Table (A-14) Pairwise Comparisons of Fairness and Accuracy by decision type and issue area

Decision Type	**Issue Area**	**Fairness**	**Accuracy**	**p-value**
Assist Collectives	Average	0.564	0.573	0.370
	Fire stations	0.571	0.566	0.717
	Homeless Shelters	0.557	0.580	0.103
Assist Individuals	Average	0.432	0.375	0.000
	Food stamps	0.396	0.327	0.000
	Study assistance	0.468	0.424	0.013
Sanction Collectives	Average	0.373	0.464	0.000
	Construction	0.358	0.437	0.000
	Immigration	0.388	0.491	0.000
Sanction Individuals	Average	0.257	0.268	0.264
	Restraining order	0.232	0.217	0.293
	Criminal Sentencing	0.281	0.318	0.008

C Policy Evaluation Experiment

C.1 Balance Tables

This section provides the demographic balance tables for the first experiment.

Table (A-15) Table (A-15) Balance Tables

Characteristic	ADS	HDS	p	ADS	HDS	p
	Homelessness			**Education**		
N	131	133		131	133	
Gender (%)			0.903			0.801
Male	66 (50.4)	65 (48.9)		61 (46.6)	65 (48.9)	
Female	65 (49.6)	68 (51.1)		70 (53.4)	68 (51.1)	
Age (%)			0.763			0.325
18–24	13 (9.9)	17 (12.8)		12 (9.2)	18 (13.5)	
25–34	21 (16.0)	24 (18.0)		31 (23.7)	19 (14.3)	
35–44	33 (25.2)	29 (21.8)		25 (19.1)	30 (22.6)	
45–54	25 (19.1)	25 (18.8)		24 (18.3)	20 (15.0)	
55–64	12 (9.2)	17 (12.8)		16 (12.2)	16 (12.0)	
65+	27 (20.6)	21 (15.8)		23 (17.6)	30 (22.6)	
Education (%)			1.000			0.139
Associate's+	51 (38.9)	51 (38.3)		60 (45.8)	48 (36.1)	
Some Col. or Less	80 (61.1)	82 (61.7)		71 (54.2)	85 (63.9)	
Race (%)			0.327			0.727
Non-White	57 (43.5)	49 (36.8)		48 (36.6)	45 (33.8)	
White	74 (56.5)	84 (63.2)		83 (63.4)	88 (66.2)	
Political (%)			0.984			0.420
Democrat	42 (32.1)	44 (33.1)		44 (33.6)	37 (27.8)	
Independent	48 (36.6)	48 (36.1)		50 (38.2)	61 (45.9)	
Republican	41 (31.3)	41 (30.8)		37 (28.2)	35 (26.3)	
Digital Literacy (%)			0.872			0.541
Low	84 (64.1)	83 (62.4)		86 (65.6)	93 (69.9)	
High	47 (35.9)	50 (37.6)		45 (34.4)	40 (30.1)	
	Policing			**Child Welfare**		
Characteristic	**ADS**	**HDS**	**p**	**ADS**	**HDS**	**p**
N	129	140		142	139	
Gender (%)			0.010			0.873
Male	68 (52.7)	51 (36.4)		62 (43.7)	63 (45.3)	
Female	61 (47.3)	89 (63.6)		80 (56.3)	76 (54.7)	
Age (%)			0.773			0.581
18–24	11 (8.5)	18 (12.9)		28 (19.7)	30 (21.6)	
25–34	28 (21.7)	25 (17.9)		26 (18.3)	28 (20.1)	
35–44	29 (22.5)	26 (18.6)		35 (24.6)	30 (21.6)	
45–54	21 (16.3)	22 (15.7)		14 (9.9)	22 (15.8)	
55–64	15 (11.6)	19 (13.6)		13 (9.2)	9 (6.5)	
65+	25 (19.4)	30 (21.4)		26 (18.3)	20 (14.4)	
Education (%)			1.000			0.923
Associate's+	55 (42.6)	59 (42.1)		58 (40.8)	55 (39.6)	
Some Col. or Less	74 (57.4)	81 (57.9)		84 (59.2)	84 (60.4)	
Race (%)			0.891			0.882
Non-White	45 (34.9)	51 (36.4)		57 (40.1)	58 (41.7)	
White	84 (65.1)	89 (63.6)		85 (59.9)	81 (58.3)	
Political (%)			0.293			0.400
Democrat	35 (27.1)	50 (35.7)		38 (26.8)	47 (33.8)	
Independent	55 (42.6)	50 (35.7)		63 (44.4)	53 (38.1)	
Republican	39 (30.2)	40 (28.6)		41 (28.9)	39 (28.1)	
Digital Literacy (%)			0.599			0.386
Low	86 (66.7)	88 (62.9)		88 (62.0)	94 (67.6)	
High	43 (33.3)	52 (37.1)		54 (38.0)	45 (32.4)	

Note: ADS = Algorithmic Decision System; HDS = Human Decision System. Apart from gender distribution in the Policing Domain ($p = 0.010$), all demographic characteristics were balanced across treatment groups in all domains ($p > 0.05$).

C.2 Average Treatment Effects

Table (A-16) Effects of ADS on the Support for Policy Proposals

Domain	Estimate	Std.Error	Statistic	P.Value	Conf.low	Conf.high
Public Housing	0.107	0.061	1.758	0.080	-0.013	0.227
Education	0.137	0.061	2.247	0.025	0.017	0.257
Policing	-0.143	0.061	-2.356	0.019	-0.262	-0.023
Child Welfare	-0.121	0.056	-2.150	0.032	-0.232	-0.010

Table A-17 assesses the possibility that using algorithmic systems to assist, rather than human decision makers, has a different effect on attitudes. The table below reports the results of a linear probability model, estimating the effects of the two conditions relative to the control condition of the human decision maker. The results show that there are no significant differences between these two conditions across all policy domains, except policing.

Table (A-17) ADS versus HDM assisted by ADS

Domain	Estimate	Std.error	Statistic	P.value	Conf.low	Conf.high
Public Housing	0.011	0.061	0.176	0.861	-0.109	0.130
Education	-0.012	0.060	-0.205	0.838	-0.131	0.107
Policing	-0.250	0.061	-4.080	0.000	-0.370	-0.129
Child Welfare	-0.031	0.056	-0.551	0.582	-0.141	0.079

C.3 Robustness Checks

C.3.1 Full Sample Analyses

To learn about the respondents' initial reactions and to address potential priming effects, the main analysis limits the sample to include responses collected by the first scenario. The results are reported in columns 1,5,9,15 of Table A-18. Columns 3,7,11,17 report estimates based on the full sample, controlling for the presenting order of the vignettes. The results remain in the same direction. Furthermore, in the main text, I presented the basic average treatment effect estimate, leveraging only the random assignment for identification. As pre-registered for the secondary analysis, Columns 2,4,6,8,10,12,14,16 report results, including the covariates. The addition of covariates makes almost no difference in the estimate of the treatment effects. The models show that the findings are robust when controlling for both fast, inattentive respondents who rush through surveys and slow, inattentive respondents who may be distracted and exhibit longer response times.

Table (A-18) Additional Results

	Dependent variable:															
	Public Housing				Child Welfare				Public Education				Police Patrolling			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
ADS	0.107†	0.115†	0.048	0.048	−0.121*	−0.127*	−0.078**	−0.073**	0.137*	0.133*	0.116***	0.116***	−0.143*	−0.135*	−0.098**	−0.098**
	(0.061)	(0.060)	(0.031)	(0.030)	(0.056)	(0.055)	(0.029)	(0.028)	(0.061)	(0.061)	(0.031)	(0.031)	(0.059)	(0.060)	(0.030)	(0.030)
HDM assisted by ADS	0.096	0.108†	0.057†	0.057†	−0.090	−0.063	−0.054†	−0.043	0.149*	0.151*	0.112***	0.112***	0.107†	0.108†	0.020	0.019
	(0.061)	(0.061)	(0.030)	(0.030)	(0.058)	(0.057)	(0.028)	(0.027)	(0.061)	(0.061)	(0.030)	(0.030)	(0.061)	(0.062)	(0.030)	(0.030)
Female		0.080		0.025		−0.025		−0.021		0.065		0.033		−0.013		−0.019
		(0.050)		(0.025)		(0.046)		(0.023)		(0.051)		(0.025)		(0.051)		(0.025)
Age		−0.002		−0.001		−0.004**		−0.001		−0.002		−0.001		0.002		0.001
		(0.002)		(0.001)		(0.001)		(0.001)		(0.002)		(0.001)		(0.002)		(0.001)
Some college or less		0.117*		0.102***		0.068		0.043†		0.021		0.025		0.027		0.011
		(0.054)		(0.027)		(0.049)		(0.024)		(0.054)		(0.027)		(0.053)		(0.026)
White		0.041		−0.021		0.040		−0.120***		0.070		0.009		−0.098		−0.008
		(0.061)		(0.030)		(0.054)		(0.027)		(0.061)		(0.030)		(0.060)		(0.030)
Independent		−0.102		−0.073*		0.030		−0.032		−0.068		−0.024		−0.034		−0.064*
		(0.063)		(0.031)		(0.056)		(0.028)		(0.061)		(0.031)		(0.061)		(0.030)
Republican		0.032		−0.013		0.087		0.037		−0.107		−0.057†		−0.012		0.007
		(0.067)		(0.033)		(0.061)		(0.030)		(0.068)		(0.034)		(0.066)		(0.033)
High Tech Literacy		0.052		0.065*		0.163**		0.169***		0.007		0.066*		0.114*		0.125***
		(0.057)		(0.029)		(0.053)		(0.026)		(0.060)		(0.029)		(0.057)		(0.029)
Inattentive		−0.056		−0.054		0.078		0.118***		0.005		−0.026		−0.007		0.061†
		(0.073)		(0.036)		(0.065)		(0.033)		(0.077)		(0.037)		(0.071)		(0.036)
Order			−0.008	−0.007			−0.010	−0.010			0.006	0.004			−0.022*	−0.021*
			(0.010)	(0.010)			(0.010)	(0.009)			(0.010)	(0.010)			(0.010)	(0.010)
Constant	0.511***	0.466***	0.543***	0.551***	0.403***	0.418***	0.393***	0.408***	0.474***	0.537***	0.445***	0.464***	0.600***	0.548***	0.653***	0.579***
	(0.043)	(0.118)	(0.034)	(0.063)	(0.040)	(0.097)	(0.032)	(0.057)	(0.043)	(0.113)	(0.035)	(0.063)	(0.041)	(0.121)	(0.034)	(0.062)
Observations	394	394	1,582	1,582	409	409	1,582	1,582	394	394	1,582	1,582	385	385	1,582	1,582
R^2	0.010	0.049	0.003	0.026	0.012	0.085	0.006	0.103	0.019	0.038	0.012	0.021	0.041	0.068	0.014	0.037

Notes: This table reports estimates from LPM. The base category of the independent variable is the human decision-maker (HDM).†p<0.1; *p<0.05; **p<0.01; ***p<0.001

C.3.2 Alternative Measures of Outcomes

To easily interpret the ATE as the percentage change in public support for a policy proposal as a result of the usage of ADS, I coded the outcome as a binary variable that takes the value "1" if the respondent "strongly" or "somewhat supports" the policy and 0 otherwise. As preregistered for the secondary analysis, I replicate the results, using an alternative outcome that measures support as a five-point scale (Columns 1-4) and as binary variable for strongly support' (Columns 5-8. The table below shows that all conclusions remained the same when I measured support for policy proposal as a scale with five values.

Table (A-19) Alternative Measures of Outcomes

	Dependent variable:							
	Support (5-point)				Strongly Support			
	(Housing)	(Child)	(Education)	(Policing)	(Housing)	(Child)	(Education)	(Policing)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ADS	$0.258^{\dagger}$	-0.350^{*}	0.309^{*}	-0.368^{**}	0.102^{*}	-0.053	0.011	-0.131^{*}
	(0.144)	(0.166)	(0.153)	(0.138)	(0.051)	(0.040)	(0.052)	(0.052)
HDM assisted by ADS	$0.247^{\dagger}$	$-0.296^{\dagger}$	0.352^{*}	0.142	0.073	-0.041	0.020	0.016
	(0.144)	(0.171)	(0.154)	(0.142)	(0.051)	(0.041)	(0.052)	(0.054)
Constant	3.376^{***}	2.914^{***}	3.256^{***}	3.686^{***}	0.165^{***}	0.158^{***}	0.218^{***}	0.286^{***}
	(0.101)	(0.118)	(0.108)	(0.096)	(0.036)	(0.028)	(0.037)	(0.036)
Observations	394	409	394	385	394	409	394	385
R^2	0.010	0.012	0.016	0.034	0.011	0.005	0.0004	0.023
Note:								†p<0.1; *p<0.05; **p<0.01; ***p<0.001

C.3.3 Interaction Between Decision-maker and Context

To assess whether the decision type moderates the effect of ADS on the evaluation of policy proposals, I examine the interaction effect of the decision-maker and the decision type treatments on support. The table below reports the results of logistic regression models in which the probability of supporting the policy proposal is regressed on the decision type (4-category variable capturing the policy proposal presented first), the decision-maker (3-category variable capturing HDM, ADS, and HDM assisted by ADS), and their interaction. The base categories of the key variables are the policy of child-abuse allegations and HDM. Thus, the last row reports the baseline probabilities of support for the proposal to prioritize child abuse investigations by human decision-makers (child welfare workers). The analysis is based on data collected from all scenarios presented first for the respondents.

Table (A-20) Interaction - Policy context and Decision maker

	Dependent variable:			
	(binary, 2 last cat)		(5-point scale)	
	(1)	(2)	(3)	(4)
ADS X Education	0.258**	0.253**	0.660**	0.641**
	(0.083)	(0.083)	(0.213)	(0.212)
ADS X Policing	−0.021	−0.012	−0.018	0.007
	(0.083)	(0.082)	(0.212)	(0.211)
ADS X Public Housing	0.228**	0.232**	0.608**	0.608**
	(0.083)	(0.083)	(0.213)	(0.212)
ADS	−0.121*	−0.120*	−0.350*	−0.346*
	(0.058)	(0.058)	(0.148)	(0.147)
Education	−0.090	−0.080	−0.296†	−0.266†
	(0.059)	(0.059)	(0.152)	(0.152)
Policing	0.240**	0.225**	0.649**	0.606**
	(0.084)	(0.084)	(0.216)	(0.215)
Public Housing	0.197*	0.177*	0.438*	0.383†
	(0.085)	(0.085)	(0.218)	(0.218)
ADS+HDS X Education	0.187*	0.175*	0.544*	0.514*
	(0.084)	(0.084)	(0.216)	(0.215)
ADS+HDS X Policing	0.071	0.083	0.342*	0.383*
	(0.059)	(0.059)	(0.151)	(0.150)
ADS+HDS X Public Housing	0.197***	0.199***	0.772***	0.782***
	(0.058)	(0.058)	(0.149)	(0.148)
ADS+HDS	0.108†	0.110†	0.462**	0.475**
	(0.059)	(0.059)	(0.151)	(0.150)
Age		−0.002*		−0.004*
		(0.001)		(0.002)
Female		0.030		0.101
		(0.025)		(0.063)
Independent		−0.045		−0.096
		(0.030)		(0.077)
Republican		−0.001		0.001
		(0.033)		(0.084)
Some college or less		0.052*		0.099
		(0.026)		(0.067)
White		0.017		−0.072
		(0.029)		(0.074)
High Digital Literacy		0.084**		0.178*
		(0.027)		(0.070)
Constant	0.403***	0.405***	2.914***	2.994***
	(0.041)	(0.064)	(0.105)	(0.163)
Observations	1,582	1,582	1,582	1,582
R^2	0.066	0.081	0.097	0.114

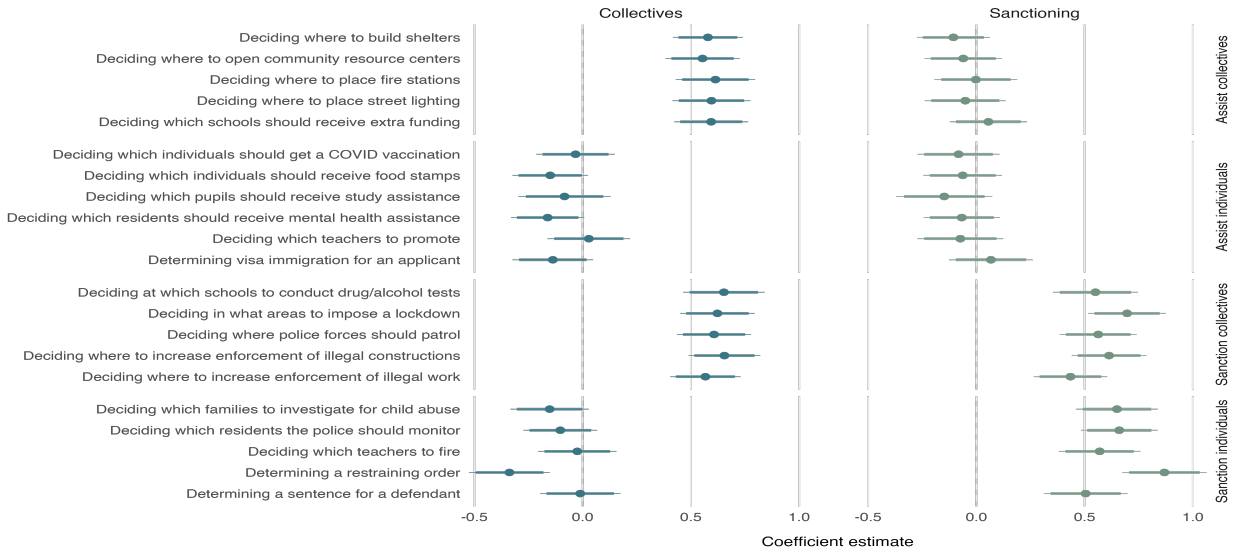
Note:
†p<0.1; *p<0.05; **p<0.01; ***p<0.001

D Validating the Theory Using MTurk Data

I tested the validity of the theoretical classification using survey data from MTurk (N=150).

Respondents were presented with a matrix of randomly selected decisions (six out of 19 decisions) and asked to classify each of the decisions into one of four decision types derived from the theory: assisting individuals, assisting collectives, sanctioning individuals, or sanctioning collectives. Notable, I provided no information about the identity of the decision-maker—whether decisions were made by humans or algorithms, as the main goal was to confirm that people do indeed agree with the theoretical classification of policy decisions into two be two dimensions.[28]

Figure (A-4) Empirical Validation of the 2x2 Classification



Figures A-4 show estimates of linear probability models that include fixed effects for each respondent. Figure A-4 (a) shows the probability of classifying each decision as aim to sanction rather than assist while Figure A-4 (b) displays the probability of classifying each decision as target collectives rather than individuals. Thick bars represent 90% CI; thin bars represent 95% CI. The original classification of the questions, as defined by the theory, is indicated on the right side of the figure. Since each respondent evaluated a random subset of six decisions from the pool of decisions, the baseline in the model is not a specific decision category but rather each respondent's own average response across the six decisions they evaluated. Therefore, each decision's coefficient compares its likelihood of being classified as targeting collectives rather than individuals in Model (a) or as sanctioning rather than

[28] The exact wording of the question was as follows: "Next, we will present you with several decisions. These decisions differ by: (1) What they aim to do: decisions that assist by providing social services or goods; and decisions that sanction by limiting lives or opportunities. (2) To whom they apply: decisions that apply to individuals and decisions imposed on collectives such as communities or areas. Please indicate which category best describes each of the following decisions."

assisting in Model (b) relative to the average classification across the decisions evaluated by each respondent.

The results are consistent with the theoretical classification. The figure shows that all (and only) decisions originally classified by the theory as targeting collectives have positive, statistically significant, and substantively large estimated coefficients. On average, these coefficients are statistically significantly different from the coefficients of decisions originally classified as targeting individuals, suggesting that respondents do distinguish between these decisions. Similar findings are observed in the model regressing the probability of defining decisions as sanctioning rather than assisting.

Furthermore, examining the proportion of respondents who classified each decision according to the theoretical classification reveals that respondents generally align with the two theoretical dimensions when categorizing policy decisions, with agreement levels ranging from 53% to 93%. While some variation exists in the level of agreement with the theoretical classification, this variation is not heavily biased towards any particular type of decision. Therefore, the 2x2 framework offers a useful initial structure for understanding contextual variation in preferences. These distinctions could be further studied as a continuum.

E Research Ethics

The study is based on a survey administered by the survey company Dynata (previously known as SSI). The survey was reviewed and approved by IRB before the study was initiated (protocol numbers: 0004542-1). It was complied using the current standards for research transparency and ethics, including the American Political Science Association's "Principles and Guidance for Human Subjects Research" as approved by the APSA Council in April, 2020. Informed consent was obtained from each participant at the beginning of the survey. Specifically, respondents were informed that (1) the survey was voluntary, (2) they could exit it at any time without penalty, and (3) they were free to decline to answer any particular question. Respondents were reimbursed by the survey firm with standard compensation. Moreover, the survey companies did not provide any identifying data, such as names or email addresses, so the data used in the analysis and provided for the replication would be anonymous. Finally, the policy proposals that respondents were asked to evaluate were based on real initiatives to incorporate AI technologies. This means that the experiment did not include false information.

F Pre-registration

This study was pre-registered on OSF (EGAP Registration ID: 20220323AA) on March 23, 2022 in a non-anonymous version. This section includes a blind version of the pre-registration. Note that the pre-registration report includes 3 experiments, but only 2 of them are relevant for this paper.

Is this Registration Prospective or Retrospective? Registration prior to any research activities.

Is this an experimental study? Yes.

Date of start of study 23/04/2002.

Was this design presented at an EGAP meeting? No.

Background and explanation of rationale. In this project, I seek to understand how people respond to the growing use of algorithmic decision systems (ADSs) in public policy and to explain variations in preferences across policy domains and decision types. I will do so by (1) developing a theoretical framework to account for variations in views on the fairness, accuracy, and legitimacy of ADSs across decision types and (2) subjecting the theory and its implications to empirical tests using novel data from three experiments embedded in a national representative survey of the US population.

What are the hypotheses to be tested/quantities of interest to be estimated? If people are, as previous studies have suggested, algorithm averse, we would expect that, when asked directly, citizens will prefer that a human being rather than an algorithm make high-stake decisions in the public sector. However, people's preferences over human decision-makers (HDM) would not translate uniformly into less support for policy decisions that rely on algorithmic assessment. The sensitivities people have toward the use of ADS differ depending on the decision type in which it is deployed. I propose classifying decisions in the public sector along two dimensions that I consider relevant to the way we define a correct or incorrect decision and the consequences of that decision. The first dimension relates to the population directly affected by the decision (individuals vs collectives). The second dimension relates to the broader objective of the decision (assisting vs sanctioning). In decisions about collectives, the reliance on big data to draw predictions about aggregate cases will be perceived as highly accurate when compared with predictions on individuals, wherein the dependence upon bigdata may be perceived as less accurate because it is more vulnerable to errors in the context of certain cases (more specifically, borderline or marginal cases). Due to the perceived lack of subjectivity surrounding algorithms, they may be perceived to be fairer in assisting decisions that provide public goods and services. However, this exact lack of subjectivity makes ADSs be perceived less appropriate when they are used in the context of sanctioning decisions, which may have irreversible consequences that limit individual or collective lives.

Based on this theory, I put forth the following expectations about variations in people's views across these dimensions: (1) People will be less sensitive to the use of ADS in decisions on collective cases versus individuals. (2) People will be more supportive of the use of ADS in decisions that assist collectives versus punish collectives. (3) When there is a tradeoff between fairness and accuracy, people are likely to be less tolerant to ADS in decisions that entail irreversible consequences.

How will these hypotheses be tested? To test the hypotheses outlined above, I designed a survey that compromises three experiments (A flow diagram of the survey experiment is provided below).

To assess whether and how algorithmic decision-making, compared to human decision-making, affects the evaluation of policy decision-making, the first experiment manipulates the decision-maker (ADS), a human decision-maker (HDM), and an HDM assisted by an ADS).

The third experiment is designed to assess the theory I developed to explain variation in attitudes across the two dimensions: (1) the broader objective of the decision (assisting versus sanctioning decisions) and (2) the subject who will be affected by the decision (individuals versus collectives). Respondents will be asked to express their opinion on the use of ADS in 7 randomly selected decision contexts presented in a matrix. The section is composed of two designs: between and within-subjects.

A between-subjects design: To assess variation in people's sensitivities to ADS within policy domains, the first three decisions in the matrix ask on three fixed policy domains: policing, child welfare, and education, where the type of decision in each policy domain is randomly assigned into 1 our of 4 types of decisions derived from the theory I developed: assisting individuals, assisting collectives, sanctioning individuals or sanctioning collectives.

A within-subjects design: The matrix includes 4 additional decisions (1 out of 2) in each of the four decision types: assisting individuals, assisting collectives, sanctioning individuals or sanctioning collectives, where the policy domain is randomly assigned.

Before the treatments are allocated, I will collect demographic information (birth year, race/ethnicity, and education). I will also ask two attention check questions (one before the first experiment and one before the second experiment). If respondents fail those attention checks, they are removed from the survey. All randomizations of the survey elements (listed below) will take place at the level of the individual respondent. Conditions will be randomly assigned with equal probability using random number generation within Qualtrics survey software.

How will these hypotheses be tested? The target sample size is 1,500 in the United States. A sample size of 1,500 respondents will allow us to detect an effect size of approximately 0.2 standard deviations at the standard 0.05 alpha error probability in the experiment with the largest number of conditions (using the conventional 80% power level).

Country United States.

Sample Size (of Units) The target sample size is 1,500 in the United States. A sample size of 1,500 respondents will allow us to detect an effect size of approximately 0.2 standard deviations at the standard 0.05 alpha error probability in the experiment with the largest number of conditions (using the conventional 80% power level).

Was a power analysis conducted prior to data collection? Yes.

Has this research received Institutional Review Board? Yes.

IRB Number 0004542-1.

Date of IRB Approval 13-02-2022.

G Pre Analysis Plan

1. Policy Evaluation Experiment Assessing the hypothesis that people's preferences over human decision-makers would not translate uniformly into lower support for policy decisions that rely on algorithmic assessment.

1.1. Primary analyses: (a) For each of the four policy proposals, I will compute the average support (the main outcome) and standard deviations across the two key experimental groups (HDM and ADS). (b) For each of the four policy proposals, I will compute the average treatment effect (ATE) of ADS versus HDM and its standard error.

1.2. Secondary analyses: (a) I will compute the ATEs of ADS vs. HDM and vs. HDM assisted by ADS (HDM+ADS). (b) I will report estimates from OLS regression models adjusting for respondents' socio-demographic characteristics: gender, age, race, and education, in order to improve the precision of estimates. I do not expect the inclusion of these covariates to meaningfully change the size of estimated effects – just the size of the standard errors. (c) I will report estimates from OLS regression models using alternative measures of the outcome variable (see secondary outcomes).

1.3 Explanatory analyses: I will report the conditional marginal effects of decision-maker and policy context, using OLS models regressing the outcome on dummies for each treatment -decision-maker and policy context – and their interaction. The analysis will be based on the data collected from the first policy proposal randomly presented to the respondent. Note that the key aim here is only to provide suggestive evidence for the variation in people's sensitivities to the use of AI across contexts. A more nuanced examination of this variation is provided in the third part of the survey, which is designed to assess the theory I developed.

2. Decision Type Experiment Analyzing in more depth the theory of variation across decision contexts.

2.1. Between-subjects analysis

2.1.1. Primary analyses (a) For each of the three policy domains, I will compute the average of the three primary outcomes and standard deviations across the four types of decision: assisting individuals, assisting collectives, sanctioning individuals, sanctioning collectives. (b) For each of the three policy domains, I will calculate the ATEs of the four types of decisions. Specifically, I will report estimates from OLS regression models studying the effect of the type of the decision on the probability to view the use of ADS as (1) appropriate, (2) fair, (3) accurate, leaving sanctioning collective as the reference category.

2.1.2 Secondary analyses (a) I will report estimates from OLS regression models adjusting for respondents' socio-demographic characteristics: gender, age, race, education, party affiliation, technological orientation. I do not expect the inclusion of these covariates to meaningfully change the size of estimated effects – just the size of the standard errors. (b) I will report estimates from OLS regression models using alternative measures of the outcome variables (see secondary outcomes). (c) For each of the three policy domains, I will report estimates from OLS regression models studying the interaction between the two theoretical dimensions. I will report estimates from OLS models regressing the three outcomes (appropriate, fair, accurate) on dummies for each of the two theoretical dimensions – the objective of the decision (assisting or sanctioning) and the subjects of the decision (individuals or collectives) – and the interaction between them. The analysis will

be based on the data collected from the first policy proposal randomly presented to the respondent.

2.3. Within-subjects analysis

2.3.1. Primary analyses (a) I will compute the average of the three primary outcomes and standard deviations across the four types of decisions. (b) I will report estimates from OLS regression models studying the independent predictive role of each theoretical dimension – the objective of the decision (assisting or sanctioning) and the subjects of the decision (individuals or collectives) on the three outcomes of interest. The model will include fixed effects for respondents.

2.3.2. Secondary analysis: I will report estimates from OLS regression models adjusting for respondents' socio-demographic characteristics: gender, age, race, education, party affiliation, technological orientation, and using alternative measures of the outcome variables (see secondary outcomes). I will also check for heterogeneity in people's attitudes based on demographics and general trust in traditional DM and AI technology.