Do Algorithms Know All? Civilians' Perception of Employing Artificial Intelligence in Government Decisions*

Dongfang Gaozhao[a], James E. Wright II[a], and Mylah K. Robinson[b]

[a]Askew School of Public Administration and Policy, Florida State University
[b]Florida Commission on Offender Review

Abstract

Artificial intelligence (AI) is increasingly being used in public service delivery. This presents several questions still left unknown about how civilians view the use of AI. In particular are their perceptions of AI and automated decisions different from those of public employees and human decisions? This paper begins to answer this by conducting a conjoint experiment to investigate civilians' preference and evaluation of decisions made by bureaucrats and by AI. Our results show that individuals generally prefer a racially minoritized government agent with a longer training history to deliver public services. This is particularly true for racially minoritized civilians who care about representation. However, when representation within the bureaucracy is not possible, racially minoritized individuals do not have a clear-cut preference between AI and out-group bureaucrats. Our findings provide insight into the interaction between automation, representation, and equity in the delivery of public services.

Keywords: artificial intelligence, algorithms, automation, administrative decision-making, discretion, representation, equity

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Dongfang Gaozhao is a Ph.D. candidate in the Askew School of Public Administration and Policy at Florida State University. His research primarily focuses on digital governance, citizen engagement, performance management, and social equity. James E. Wright II is an assistant professor in the Askew School of Public Administration and Policy at Florida State University. His research interests center around public management, public policy and social equity. Mylah K. Robinson is a revocation specialist in the Florida Commission on Offender Review.

1 Introduction

Traditional public administration decisions have consisted of a public servant interacting with a civilian to determine the best course of action for the civilian. However, there has been a recent push to use artificial intelligence (AI) and algorithms[1] to help facilitate public organization decision-making. As part of this push for increased automation, scholars argue that automation can increase organizational performance and increase efficiency in administrative decision-making (Zekić-Sušac et al., 2021). Moreover, scholars argue that the use of automation will help administrators provide "better public services" while continuing to professionalize the public service (Lindgren et al., 2019). One such example is the use of machine learning techniques to provide image or handwriting recognition, which is then used to create chains of automation for straightforward tasks (Veale & Brass, 2019).

As automation has increased in usage in everyday society, public administration has adopted it within the field as well. For example, applications for social welfare programs (such as unemployment benefits), government services (such as trash pick-up and pothole repair) and requiring permits has moved to e-platforms (Gil et al., 2019). In practice, when individuals fill out forms electronically for social benefits, there are two systems behind a computer screen to review applicants and applications: public employees and algorithms. In some cases, algorithms start to work before human reviewers may step in—to screen out unqualified applicants to facilitate the decision-making process. As processes like this become more salient within public administration, this drastically changes the operation and scope of administrative decision-making (Bullock, 2019), which is the heart of public administration (Simon, 1947). As automation becomes normalized within the field, understanding how it shapes equity in outcomes and representation is an important aspect yet to be explored.

While proponents argue that automation can increase efficiency, the field has yet to substantially explore how civilians view automation in terms of equity. Recent literature has explored the relationship between automation and equity (Miller & Keiser, 2021) and found that traditional under-resourced communities prefer automation but only in a traditionally antagonist public profession (policing), between communities of color and public service. However, given the proliferation of automation in public service delivery, understanding who benefits the most from automation and if efficiency *and* equity can co-exist in multiple public services areas is important. In an attempt to begin to unpack this our paper investigates civilians' evaluation of decisions made by bureaucrats and by AI.

In particular we employed a conjoint experiment. In the experiment, participants weighed two options to deal with the quality of social welfare applications, namely assigning public employees to conduct quality control reviews or deploying a set of AI-powered algorithms to do this task. We randomized reviewer's attributes and asked participants to indicate their preference and predict each reviewer's performance in terms of efficiency, consistency, and ability to apply equity. The results show that individuals generally prefer a public employee who is an African American female, with 5-6 years of training, to serve as the quality control reviewer. For African American participants, if they cannot choose an African American bureaucrat to be their reviewer, they

[1] Technically, "artificial intelligence" refers to "the capability of a machine to imitate intelligent human behavior" (Merriam-Webster, 2021b) whereas "algorithms" are a set of rules that a machine follows to achieve a particular goal, e.g., imitating human intelligence (Merriam-Webster, 2021a). In this paper, for the sake of readability, we use "artificial intelligence (AI)" and "algorithms" interchangeably.

may treat other bureaucrats and AI the same. In addition, we find that people believe that AI is better than public servants regarding efficiency, but inferior to the latter in terms of applying equity.

The rest of the paper is organized as follows. We first review the literature on people's perceptions of bureaucrats' and AI's performance and discretion. Then, we describe the experimental design and methods. After this section, we report our analysis and results, followed by a discussion of our findings' implications and contributions.

2 Literature Review

2.1 Perceptions of Bureaucrats' and AI's Performance and Discretion

People's perceptions of bureaucrats' and AI's performance and discretion matter for a variety of reasons. Understanding these perceptions clarifies the role of public administration in sustaining and utilizing citizen support of democracy, which is vital to maintain societal order while ensuring satisfaction and receipt of high-quality services (Ariely, 2013). Even in non-democracies, authorities should care about civilians' perceptions because one of their roles is to keep people from feeling dissatisfied with the government, forming collective expression, and starting factions against the government (King et al., 2013). Ariely (2013) posits that citizen satisfaction with the government can be explained by people's perceptions of public administration, which highlights the role of bureaucracy. By taking their role more seriously, bureaucrats have an opportunity to improve the quality of their services and civilians' perceptions thereof. As Chingos (2012, p. 416) has noted, "citizen perceptions of the quality of government services reflect objective measures of performance of the specific institution providing the service". In other words, the government should care about people's perceptions because they provide feedback that can positively affect services rendered. In a long run, paying attention to people's needs and perceptions cultivates public trust and satisfaction, leading to a higher willingness to coproduction and compliance with future policies among civilians (Im et al., 2014).

Many factors may influence civilians' perception of bureaucrats' performance. Scholars have found that better performance outcomes are positively associated with people's evaluation (Aytaç, 2021; Porumbescu et al., 2019). Performance may be affected by things like years of training, professionalism, and public personnel management. Dermol and Čater (2013) believe that years of training has an impact on public administrators by making them more professional and causing better performance outcomes.

That said, actual performance is not necessarily equal to perceived performance due to differing opinions on the need for and definition of public service performance (Van de Walle & Bouckaert, 2003). People's evaluation of government employees' performance is also associated with the administrative process, e.g., fairness and respect (Van Ryzin, 2015), politics and ethics (Vigoda-Gadot, 2006), and administrative autonomy (Song et al., 2021). The administrative process can help or hinder a civilians' belief in and support of a public servant and agency. Van Ryzin (2015) determines that the administrative process matters to civilians' trust of local government, which is a valuable asset to create a sense of loyalty. Yet, if there are flaws in the administrative process, the impact on civilians' trust and perceptions would be negative.

When disentangling civilians' views on the potential use of AI to replace public employees in the government decision-making process, a key factor to consider is how civilians perceive the way bureaucrats handle this issue. Civilians judge administrative agencies as fairer and more trustworthy when bureaucrats take affirmative steps towards benefitting disadvantaged groups (Riccucci & Van Ryzin, 2017). Additionally, some researchers assert that symbolic representation is likely to influence individuals' attitudes toward legitimacy and fairness even when outcomes are unfavorable (Roch et al., 2018). Positive examples like this allow civilians to engage in a process that enhances their view of legitimacy while encouraging them to cooperate and comply with the government, which is believed to cause important policy outcomes.

Riccucci et al. (2018) find that symbolic representation can significantly affect people's evaluation of performance, trustworthiness, and fairness. For Black respondents, an increase in Black officers in a police department will lead to an increase in their overall assessment of the department, even if the department's performance gets worse, facing more complaints about police misconduct. Opposite results are found among white respondents—greater Black representation in the police department will bring negative effects to white civilians' understanding of the agency's performance, trustworthiness, and fairness. This suggests that individuals may be more open to opportunities for positive engagement when they see a symbolic representation of themselves. Another study looks into gender's effects and finds that an increase in women's representation within public organizations can lead to the achievement of key gendered performance objectives in the field of policing (R. Andrews & Miller, 2013). In regard to the perceived efficiency and consistency of government employees, gender is seen as a driving force towards these types of positive initiatives. Riccucci et al. (2016) suggested that the effects of symbolic representation on civilians' willingness to coproduce and comply may be an important causal mechanism behind previously observed correlations between representation and policy outcomes. Based on the discussion, when civilians in the administrative decision-making process are facing choices of whom they would like to interact with, we posit:

H1: Subjects will have more positive attitudes toward reviewers who share the same racial or gender identities with them.

2.2 AI is Stepping in Government Decision-making

More prominent representation in public organizations through race and gender would ultimately urge us to heavily consider the use of AI in public administration and its relationship with bureaucrats, i.e., whether automation would limit interactions between civilians and public servants who have the potential to represent clients through shared social origins. On the other hand, AI technologies are widely employed in today's world, ranging from chatbots using natural language processing, algorithm-driven marketing, to medical image analysis, fraud prevention, security and monitoring services involving facial recognition (Brundage et al., 2018). In the public sector, AI meets the needs of smart government (Vogl et al., 2020) and has been used in courtrooms to predict recidivism (Van Dam, 2019), in university admissions to predict student performance (Moody, 2020), and in social welfare programs to determine eligibility (Martinho-Truswell, 2018). Depending on contexts and tasks, AI is presumably complementing, supplanting, or cooperating with human capabilities to make decisions.

While the use of AI is expanding at an unprecedented rate, our theories in the field of public administration have not grappled with this trend (Liu & Kim, 2018). Only in recent years, related studies have grown and touched on the potential impacts that AI may bring to public administration (e.g., L. Andrews, 2019; Busuioc, 2020; Wirtz et al., 2019; Young et al., 2019). These impacts include both the bright side, such as better cost efficiency and restricted individual prejudice (Wirtz et al., 2019; Young et al., 2019), and the dark side, including opacity in decision-making (Busuioc, 2020) and favoritism or unfairness due to algorithm manipulation (L. Andrews, 2019). And we will discuss AI's opportunities and challenges for public organizations and government practices with more details below. Still, it is largely unclear how civilians understand and respond to the escalating involvement of AI in public management (Sharma et al., 2020). Particularly, do people accept AI to make decisions for the government? Are people's perceptions of AI and automated decisions different from those of public employees and human decisions? These questions are critical to public managers because the answers not only closely link to people's perceptions of the government, the importance of which we have revealed above, but also directly suggest what areas public organizations can leverage AI and what areas they still need bureaucrats' discretion to foster people's trust in the government.

Two underlying assumptions here are that bureaucrat discretion and AI discretion is different and that people can tell those differences and do have a preference. While the second assumption is an empirical question that this study attempts to answer, the first assumption seems immediately obvious. Although bureaucrats and AI both work under various "rules of law," bureaucrats are motivated by self-interests and cognitively bounded whereas AI systems can be programmed to preserve "public interestedness" and process massive amounts of information within seconds (Barth & Arnold, 1999, p. 336; Simon, 1947). Such limitations in government agents make possible discretion abuse, personal bias, and bureaucratic errors (Battaglio et al., 2019; Prendergast, 2007). Even if improving bureaucrats' professionalism and representation may reduce the likelihood of discretion abuse and bias (Dermol & Čater, 2013; Hong, 2017), they cannot rule out prejudice and discrimination at the individual level, nor can they ensure consistent quality of discretion across members of the organization. From this point of view, AI discretion has some key assets that help address these problems in bureaucrat discretion and general administrative decision-making (Young et al., 2019).

For many public organizations, poor scalability is the key obstacle to improvement. In this regard, AI discretion has good scalability that can easily outpace human capacity for processing information and managing workload (Wilson & Daugherty, 2018). For example, the U.S. Citizenship and Immigration Services (USCIS) faces a class lawsuit for its long delays in handling work permits and immigration applications that are mostly caused by the limited workforce before and amid the pandemic (Wiessner, 2020; Winokoor, 2021). On the other hand, the Internal Revenue Service (IRS) and its counterparts around the world are employing AI systems to quickly detect tax evasion and noncompliance, a job that traditionally would take weeks or months by manual reviews (Rubin, 2020). Scalability allows AI to greatly increase the efficiency of public organizations, one of the pillars of public administration, and eventually improves civilians' perceptions of the government (Frederickson, 1990).

Relatedly, the highly scalable AI can provide better decision consistency. Compared to bureaucrats' decision criteria that may change from one bureaucrat to another, vary across different times, and even depend on various moods (Andersen & Guul, 2019; Eren & Mocan, 2018), AI discretion prevents government agents' personal factors from influencing the decision-making process and uses one set of algorithms to make decisions. Hence, its decisions can be more rational and consistent (Young et al., 2019). Nevertheless, this is not to say AI discretion is static and inflexible given that its machine-learning-based algorithms can evolve over time or, more specifically, hundreds of thousands of runs and simulations.

The removal of bureaucrats' personal bias has a special implication to minority civilians. In agencies where the potential for representation is limited, in policy areas in which socialization may limit the positive effects of passive representation, or if there is a lack of a critical mass of minority bureaucrats, minority civilians may be or may perceive themselves to be placed at a disadvantage in administrative decision-making. From the standpoint of bureaucrats, they may also feel unfamiliar with minority civilians' situations and cannot serve minorities' best interests. In these scenarios, automated decision-making may be beneficial (Miller & Keiser, 2021). AI can mitigate bias and enhance diversity and inclusion by being trained with loads of minorities' data and then be applied to places where bureaucrats from minority groups are hard to be recruited or where minority clients are discriminated against by local officials (Daugherty et al., 2018; H. Zhang et al., 2019). If civilians believe that unrepresentative bureaucrats are worse for them than AI, then they are likely to turn to AI to deliver services to them. For this reason, we hypothesize:

H2: Minorities will have more positive attitudes toward algorithmic reviewers when government agent reviewers do not share the same racial or gender identities with them.

2.3 AI vs. Bureaucrats, A Comparison in Multiple Dimensions

With AI being incorporated in government operation and administrative decision-making, concerns about AI discretion, discrimination, supervision, and accountability have also been raised. Brundage et al. (2018) posit a lack of deep technical understanding of AI on the part of policymakers leads to poorly designed or ill-informed regulatory, legislative, or other policy responses. These shortcomings have the potential to vastly influence public opinion on AI discretion. For example, AI discretion is increasingly autonomous and invisible, creating a black box in the decision-making process (Janssen et al., 2020). It could be difficult for civilians to understand and for public organizations to manage AI discretion in a transparent and accountable manner (B. Zhang & Dafoe, 2020).

One of the consequences is that people have double in whether automated decisions are able to fully respect the values of equity and fairness (Wachter et al., 2020). Their reservation is profoundly reasonable when considering the AI's data feeding and learning nature. The data used for training AI discretion have been well-documented skewed and contain biases and limitations, i.e., too few minorities' data points and historical inequity and discrimination that are implicit in these data (Zou & Schiebinger, 2018). As such, this can be damaging to minority groups and poor populations, exacerbating the equity concerns of (and about) the administrative decision-making (Young et al., 2019).

Taking AI's scalability, consistency, opacity, and possible data skewness into account, we hypothesize that:

H3: People will be more likely to believe, in comparison to government agent reviewers, algorithm reviewers to have better work efficiency and consistency but inferior performance on equity.

3 Research Design and Method

3.1 Experimental Design

We conducted a conjoint experiment to test our hypotheses. Conjoint experiments have been used as a powerful means to capture and estimate individuals' multidimensional preferences (Hainmueller et al., 2014; Jilke & Tummers, 2018). A typical conjoint experiment asks participants to choose a preferred profile from a group of profiles multiple times. In our case, we asked respondents to imagine that their applications for social welfare was under a review for quality control, which can be a tiresome and monotonous task to bureaucrats. Each respondent then faced three pairs of quality control reviewers and had to choose one preferred reviewer from each pair. We presented four types of attributes in these reviewer profiles, including reviewers' identity, race, gender, and year of training. Table 1 lists the attribute levels we used in the experiment. We randomized the sequence of these attributes across subjects to control for order effects but fixed the sequence within subjects to lower their cognitive burden (Hainmueller et al., 2014). While we also fully randomized reviewers' identity and year of training, it is noteworthy that we employed restrictions on reviewers' race and gender information to exclude unrealistic attribute combinations. To be specific, algorithmic reviewers cannot be African American, Caucasian, or Hispanic and should not have a male or female identity. Thus, our design bounded algorithmic reviewers with "not appliable" racial and gender identities. Correspondingly, we ruled out the possibility for government agent reviewers to have "not appliable" attributes. Our subsequent analysis has taken these restrictions into consideration.

Table 1: Conjoint Attributes and Levels

Attribute	Level
Identity	Government agent, Algorithm
Race	African American, Caucasian, Hispanic, Not Applicable
Gender	Male, Female, Not Applicable
Year of Training	Less than 1-year, 1-4 years, 5-6 years

In our experiment, we warmed participants up by asking them to assess the importance of eligibility for social welfare programs and equity to government decisions. Following these warmup questions, we presented participants with two reviewers' profiles side by side on the screen and asked them four questions that measured our dependent variables. The first question was a choice-based question in which respondents must choose one preferred reviewer from two. The question read "[w]hich reviewer do you prefer to conduct quality reviews for social welfare applications?" Participants' answers to this question will be referred to as *choice outcomes* hereinafter. After that, participants were told to predict three dimensions of reviewers' performance. We measure them to understand whether their predicted reviewers' performance influences their preference decisions. The first dimension focused on work efficiency, "how likely would these reviewers work efficiently?" Respondents evaluated the likelihood on a five-point Likert scale varying from extremely unlikely to extremely likely. Using the same scale, participants further projected reviewers' work consistency and ability to apply equity in their work. The next question read "how likely would these reviewers apply rules consistently to different people?" and the last question asked, "how likely would these reviewers apply equity when reviewing applications?" We call participants' answers to these rating questions *rating outcomes*. To control for order effects, the order of these three rating questions was randomized. As mentioned before, each participant rated three pairs of reviewer profiles. Upon the end of their evaluation, a few questions regarding respondents' characteristics were asked. Appendix A illustrates the flow of our research design.

3.2 Subject Recruitment

We pre-registered our study on Open Science Framework (OSF)[2] and targeted 1,000 participants administered through Amazon Mechanical Turk (MTurk) in October 2020. 1,301 individuals turned

[2]The pre-registration can be accessed via https://osf.io/mb7u4. Identity information in the pre-registration has been concealed for anonymity.

out to participate in our experiment. Since our focus is on the opinions of people living in the United States, we employed a protocol to detect participants with a non-U.S. IP address or a VPN connection (Winter et al., 2019) and removed them per our pre-registration. We dropped 46 subjects for this reason, 102 for their choices of withdrawal, and 139 for not completing the survey.[3] After these procedures, 1,014 respondents became our final sample.

These respondents were representative and diverse in terms of their characteristics. Our sample has 39.64% females and 59.27% males. More than 60% of our respondents are Caucasian and 23.39% are Black or African American. Hispanics occupy 4.14%, lower than Asian or Pacific Islanders participants by 2.76%. Young adults under 35 years old are the majority of our sample. In terms of participants' socioeconomic characteristics, both Democrats and Republicans take up approximately 40%. Our subjects have a fairly even distribution in terms of ideology as each interval from strongly conservative to strongly liberal was nearly 20%. A lion's share of our respondents holds a bachelor's degree or above. Our sample's household incomes are mostly between \$50,000 to \$74,999, accounting for 32.84%, followed by those between \$25,000 to \$49,999, whose share is roughly a quarter. We report participants' detailed demographic and socioeconomic information in Appendix B.

Since participants in our conjoint experiment were asked to evaluate three pairs of reviewer profiles, this study obtained 6 observations from each participant and $1,014 \times 6 = 6,084$ observations in total (see Hainmueller et al., 2014; Jilke & Tummers, 2018).

4 Analysis and Results

Our analysis begins with respondents' choice outcomes. By looking into the choice outcomes, we first estimate each attribute's average marginal component effect (AMCE).[4] An AMCE captures the causal effect of a reviewer's attribute on the probability that this reviewer will be the preferred one. Since each participant saw three pairs of reviewer profiles, we cluster standard errors by participant to account for the potential non-independence of their choice outcomes.

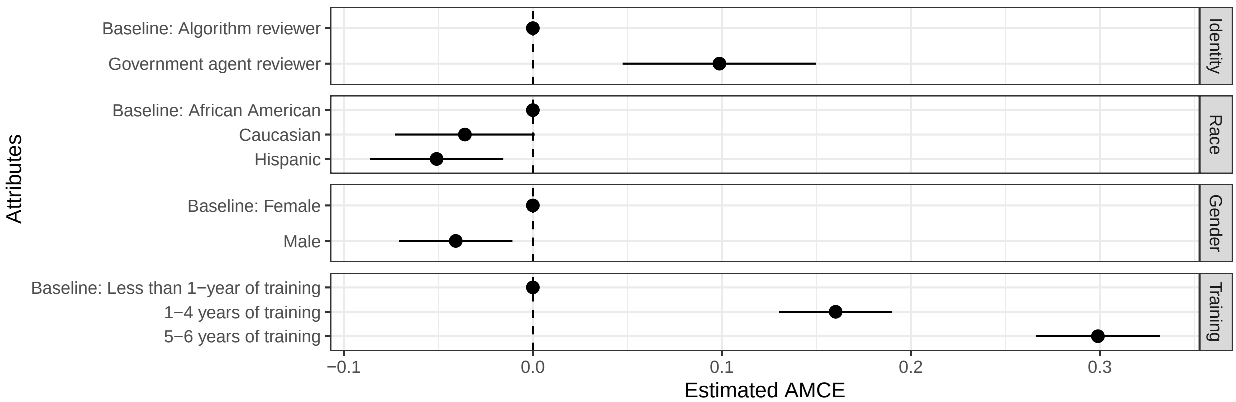
Figure 1 shows the AMCE estimates and 95% confidence intervals for each attribute level. There are six AMCE estimates relative to their baseline attributes. One may interpret these estimates as the marginal effect of each attribute level on civilians' preference of a particular reviewer. A positive AMCE indicates civilians' favorable attitudes toward the given attribute levels whereas a negative value means unfavorable attitudes toward such level. Overall, our participants gave preference to a government agent reviewer who was an African American female, with 5-6 years of training, to conduct a quality control review. In particular, participants were on average 9.9% ($SE = 0.026$) more likely to choose a government agent rather than an algorithmic agent to review their applications. With regard to reviewers' training background, substantial training provides a bonus. Reviewers who possess 5-6 years of training would be about 29.9% ($SE = 0.017$) more

[3]Most incomplete participations happened after the survey's quota on MTurk was fulfilled.

[4]For instance, the AMCE of 5-6 year of training on the probability of a reviewer being chosen as a preferred one can be derived by: (1) estimate the difference in likelihoods that two reviewers who have two different levels of training background, one being the baseline level and the other being the level of interest, but otherwise identical reviewers, are chosen to be desired; (2) compute the same difference between two reviewers with these levels of training, but with other possible combinations of profile attributes other than the year of training, i.e., algorithmic reviewers vs. government agent reviewer; and (3) calculate the weighted average of these probability differences over the joint distribution of all attributes (for the detailed estimation, see Hainmueller et al., 2014).

likely to become respondents' preferred reviewer in comparison with baseline reviewers with less than 1-year of training. Relatively, 1-4 years of training has a less significant advantage over the baseline, increasing the likelihood by 16% ($SE = 0.015$).

Figure 1: Pooled AMCE Results



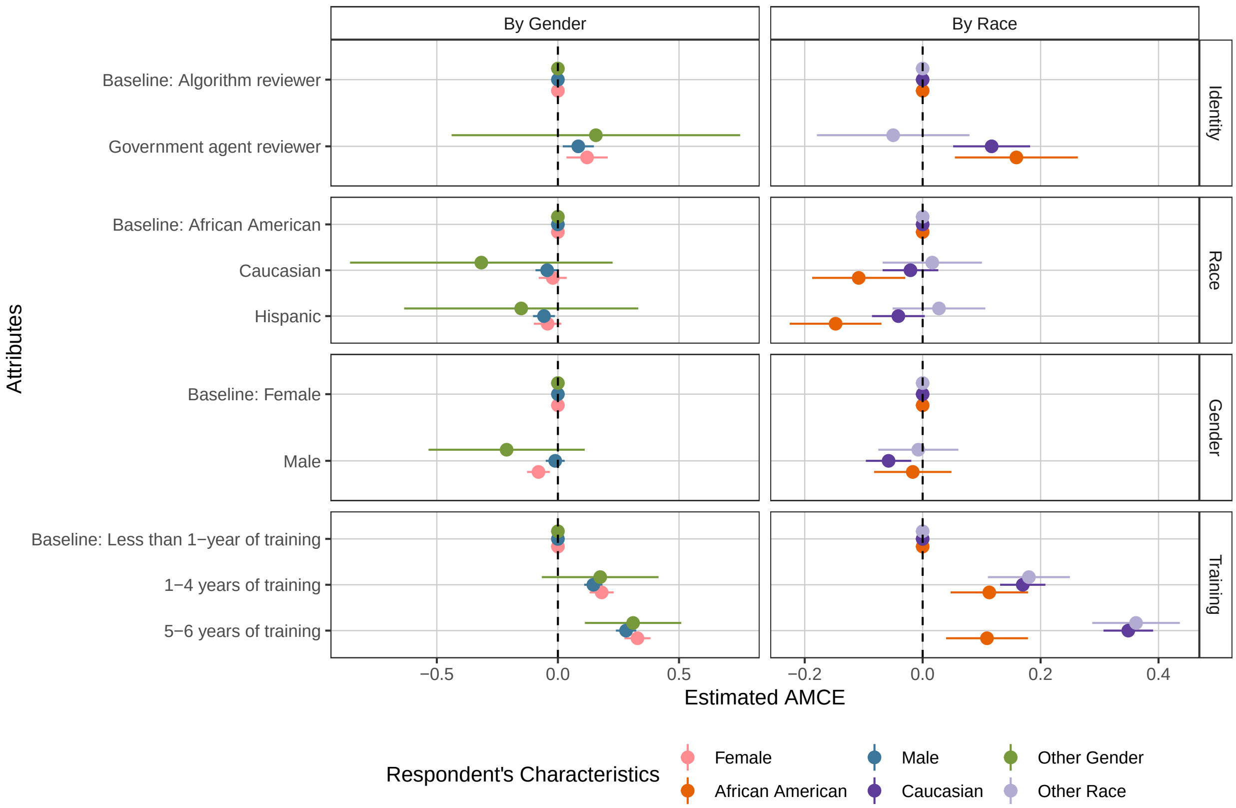
Note: Estimates are based on the regression estimators with clustered standard errors. Bars show 95% confidence intervals. Regression coefficients are in Appendix C.

Given that we added restrictions to prevent meaningless attribute combinations, we did not compare the relative effects between algorithms' non-applicable identities and government agents' gender- and race-specific identities. Instead, we examine the differences between government agent reviewers. The difference in the probability of being chosen between male and female reviewers is -0.041 ($SE = 0.015$), suggesting that females are more likely to be people's desired reviewers. For racial identities, Caucasian and African American reviewers do not have a statistically significant difference while a Hispanic reviewer is 5.1% less likely to be preferred over an African American reviewer ($SE = 0.018$).

In addition to AMCEs, we examine potential heterogeneous treatment effects, which could be caused by the respondents' characteristics. For example, an African American participant may naturally feel more connected to an African American reviewer. In other words, the causal effect of an attribute level is likely to be conditional on participants' personal characteristics. To control for this, we condition the average of the attribute's marginal effect on participants' race and gender and reported the results in Appendix D. Figure 2 visualizes the results. When interpreting them, it is worthy to mention that some subgroups in our study have relatively small sample sizes, i.e., 27 American Indian or Alaska Native participants and 42 Hispanic participants. We classify small subgroups into the "Other" categories.

With this caution in mind, we look at whether respondents' race moderates their preference decisions. The results show that African American and Caucasian participants had a strong preference for government agents over algorithms and wanted government agents to be their reviewers in the quality control process. Furthermore, African American participants showed a strong preference for African American reviewers over other human reviewers while Caucasian participants and others did not show similar in-group preference. As for the reviewer's gender, Caucasian respondents demonstrated a preference for females whereas others did not. The fourth attribute, year of training, was the most regularly used reviewer attribute. Every racial group was disinclined to have a reviewer with little training and most racial groups favor a reviewer with 5-6 years of training.

Figure 2: AMCEs by Respondents' Race and Gender



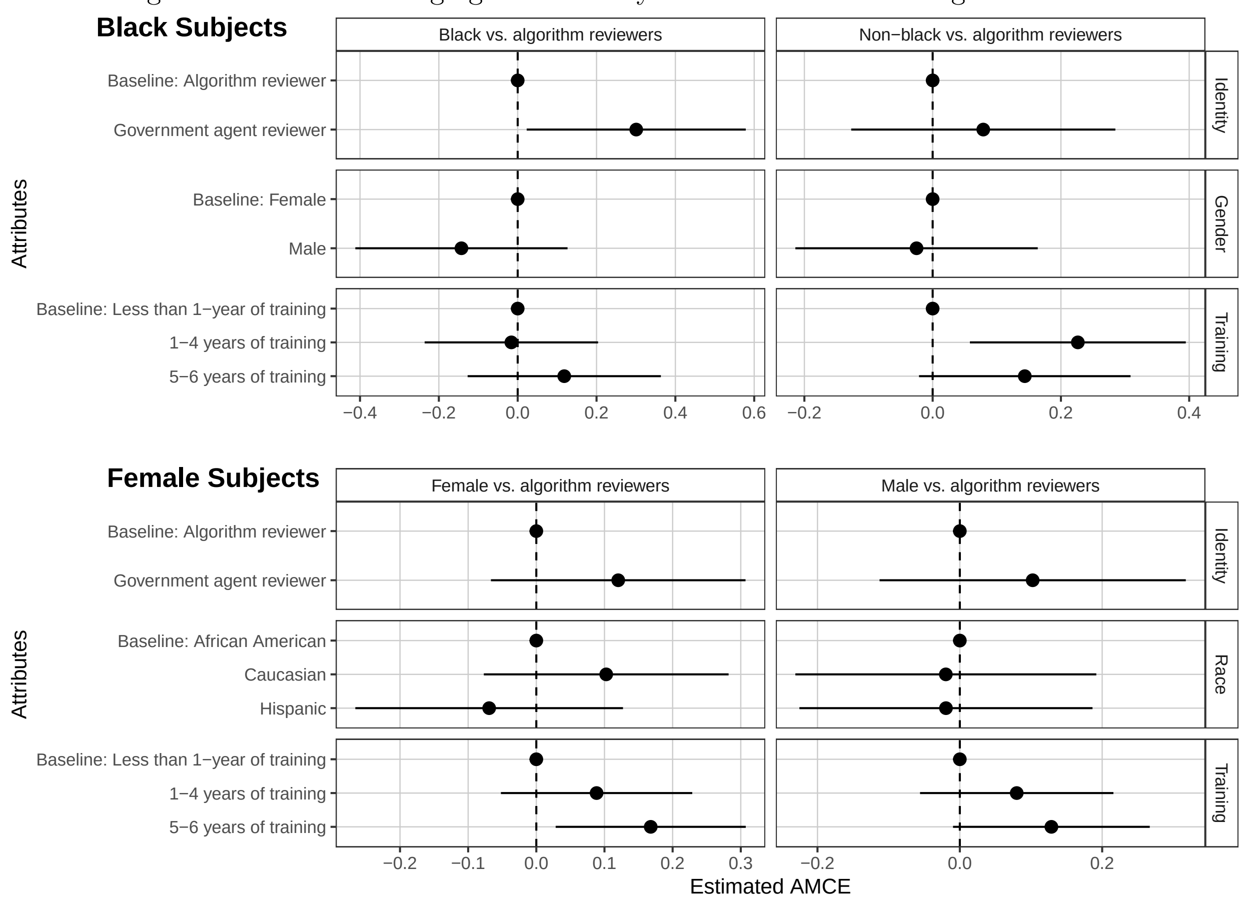
Note: Estimates are based on the regression estimators with clustered standard errors. Bars show 95% confidence intervals. Regression coefficients are in Appendix D.

Then, we investigate the effects of reviewer attributes across respondents' gender. We find a consistent preference of government agent reviewers in both male and female respondents. Moreover, male respondents reported a slight reluctance to have a Hispanic reviewer when the alternative could be a Black reviewer. Female subjects took the reviewer's gender into account and preferred female reviewers over males. Like what we have found from different racial groups, reviewers' year of training remains a crucial factor for male and female participants' preference decisions. They tended to choose reviewers with longer years of training over those with fewer years of training. These findings of racial and gender identities partially support *H1*, which expects that individuals will prefer reviewers who share the same racial or gender identities with them. Based on our results, only racially minoritized civilians care about representation and have the preference of race and gender congruence between reviewers and themselves.

Because of this preference, it is natural to ask what would happen when racially minoritized civilians do not have their preferred human reviewer and whether they would turn to prefer AI. Our *H2* posits that minorities would prefer AI reviewers when the alternative is out-group human reviewers whose race or gender identity is incongruent with them. We test *H2* with a closer look at a subset of observations in which racially minoritized respondents chose between a human reviewer and an algorithm reviewer. For this purpose, we use African American or female participants' observations because other racially minoritized categories do not have sufficient observations.

Figure 3 presents the results for racially minoritized participants' preference choices broken down by whether the government agent reviewer is passively representing the participant. When making these choices, our racially minoritized participants were offered two options: a government agent reviewer and an AI reviewer. The left facet shows the results when the government agent reviewer has a matched racial or sexual identity with the respondents. Put differently, they are passively representing the respondents. In contrast, the right facet shows the results when the passive representation is not available. As made clear by the right facet, we do not find evidence supporting *H2*, which would need statistically significant differences in racially minoritized respondents' preference between incongruent human reviewers and AI reviewers. Nevertheless, Black participants perceived little difference between out-group bureaucrats and AI taking charge of the decision-making process. For female participants in the lower panel, they did not pay too much attention to bureaucrats' social origin and treated sexually congruent and incongruent agents the same when the other option was AI reviewers.

Figure 3: Effect of Changing Attribute by Race of Government Agent Reviewer



Note: Estimates are based on the regression estimators with clustered standard errors. Bars show 95% confidence intervals. Regression coefficients are in Appendix E.

Lastly, we shift gears to three rating outcomes, namely participants' predictions of human and automated reviewers' work efficiency, consistency, and ability to apply equity when conducting quality control reviews for social welfare programs. Participants were asked to predict on a scale from 1 (extremely unlikely) to 5 (extremely likely). We dichotomize these ratings into 0 (unlikely) and 1 (likely) and then regress this binary variable on reviewer attributes as well as respondents' characteristics and priors in simple logistic regression models. For the models comparing between government agents and algorithm reviewers,

$$\text{logit}\left(\Pr\left(Y_i = 1\right)\right) = \beta_0 + \beta_1 \text{Reviewer} + \beta_2 \text{Year of Training} + \boldsymbol{\gamma}\mathbf{Control} + \varepsilon_i,$$

where $Y_i = 1$ denotes that participant i's rating is "likely." **Control** indexes a $1 \times p$ vector of respondent i's gender, race, age, party affiliation, education, household incomes, and their preexisting attitudes toward social welfare eligibility and social equity. $\boldsymbol{\gamma}$ represents a $p \times 1$ vector of the coefficients for **Control**. Similarly, for the models comparing within government agent reviewers,

$$\text{logit}\left(\Pr\left(Y_i = 1\right)\right) = \beta_0 + \beta_1 \text{Reviewer Race} + \beta_2 \text{Reviewer Gender} + \beta_3 \text{Year of Training} + \boldsymbol{\gamma}\mathbf{Control} + \varepsilon_i.$$

Table 2 demonstrates the main results. When comparing between government agents and algorithm reviewers, human reviewers are hypothesized to perform poorer than algorithm reviewers in terms of efficiency and consistency but better regarding applying equity. The results find evidence to partially support *H3*. Algorithms were perceived to be superior to government agents about efficiency and inferior about equity. However, human abilities to apply rules consistently to different people were perceived to be the same as AI. Newcomers who receive less than 1-year of training are anticipated to be inferior to those reviewers who have more years of training in all three aspects.

For differences within government agent reviewers, government agents' race and gender do not affect people's expectations of work efficiency. However, for the other two dimensions, our respondents believed that, in comparison to an African American agent, a Hispanic agent may be less consistent to apply rules whereas a Caucasian agent would be less likely to apply equity in their daily work. Similarly, people have reservations about novice government agents for their capabilities of working efficiently and consistently and applying equity to their decision-making process.

We also explored the impacts of participants' characteristics on their projection of reviewers' performance. Asians, Pacific Islanders, and those who preferred not to disclose their racial identities were less likely to have positive faith in reviewers' work efficiency, consistency, and ability to apply equity when compared to Caucasians' viewpoints. In comparison with female participants, males were less likely to believe that decision-makers in the government, either the automated or human ones, would apply rules to different people in a fair and impartial way. Latinos and multiracial people also had more doubts about reviewers' efficiency than Caucasians. Regarding people's party affiliation, we learn that Independents have a lower chance to expect AI and human reviewers to perform well on efficiency and equity perspectives if juxtaposing with Democrats.

5 Discussion and Conclusion

In this study, we conducted a conjoint experiment to compare human bureaucrats with automated decision-makers in terms of civilians' preferences and perceptions. One of the primary contributions of this study is the examination of civilians' preferences for AI versus government reviewers. We are able to disentangle individuals' preferences for the intricate attributes of human and algorithm decision-makers. Generally, we find that civilians tend to choose bureaucrats over AI to make government decisions even if the decisions to make in our case is the quality control review, a heavy, tedious, and endlessly repetitive task. In particular, civilians prefer a government agent reviewer

Table 2: Logistic Regression Main Results

Attributes	Algorithm vs. Government Agent			Within Government Agents		
	Efficiency	Consistency	Equity	Efficiency	Consistency	Equity
Intercept	0.106 (0.593)	0.200 (0.601)	0.418 (0.589)	0.130 (0.633)	0.436 (0.647)	0.170 (0.630)
Reviewer (Baseline = Algorithm)						
Government agent	0.229* (0.097)	0.013 (0.089)	0.331*** (0.087)	NA	NA	NA
Reviewer Race (Baseline = African American)						
Caucasian	NA	NA	NA	0.003 (0.085)	0.048 (0.083)	0.173* (0.083)
Hispanic	NA	NA	NA	0.061 (0.084)	0.196* (0.081)	0.059 (0.084)
Reviewer Gender (Baseline = Female)						
Male	NA	NA	NA	0.090 (0.069)	0.026 (0.067)	0.112 (0.068)
Year of Training (Baseline = Less than 1-year of training)						
1-4 years of training	0.623*** (0.078)	0.433*** (0.075)	0.252*** (0.076)	0.646*** (0.083)	0.474*** (0.081)	0.288*** (0.083)
5-6 years of training	0.737*** (0.078)	0.494*** (0.075)	0.333*** (0.076)	0.763*** (0.084)	0.505*** (0.080)	0.354*** (0.082)
Race (Baseline = Caucasian)						
American Indian or Alaska Native	0.083 (0.204)	0.393 (0.204)	0.395 (0.209)	0.106 (0.216)	0.395 (0.216)	0.316 (0.220)
Asian or Pacific Islander	0.591*** (0.122)	0.556*** (0.118)	0.624*** (0.118)	0.668*** (0.130)	0.580*** (0.127)	0.745*** (0.127)
Black or African American	0.177 (0.090)	0.155 (0.086)	0.063 (0.086)	0.181 (0.098)	0.157 (0.093)	0.034 (0.094)
Hispanic or Latino	0.402* (0.178)	0.066 (0.158)	0.265 (0.167)	0.312 (0.185)	0.006 (0.167)	0.121 (0.175)
Mixed racial background	0.468* (0.201)	0.233 (0.202)	0.214 (0.201)	0.641** (0.212)	0.366 (0.215)	0.378 (0.215)
Prefer not to answer	1.043*** (0.300)	0.977*** (0.296)	0.928** (0.300)	1.050** (0.320)	1.042** (0.315)	0.942** (0.323)
Gender (Baseline = Female)						
Male	0.083 (0.069)	0.132* (0.066)	0.042 (0.067)	0.133 (0.074)	0.189** (0.071)	0.094 (0.073)
Transgender	0.766 (0.769)	0.557 (0.651)	0.905 (0.650)	0.419 (0.792)	0.567 (0.788)	0.998 (0.788)
Prefer not to answer	0.606 (0.715)	0.773 (0.633)	0.867 (0.722)	0.500 (0.785)	0.684 (0.677)	1.336 (0.836)
Party (Baseline = Democrat)						
Independent	0.202* (0.095)	0.167 (0.090)	0.337*** (0.091)	0.222* (0.101)	0.130 (0.097)	0.302** (0.100)
Republican	0.059 (0.077)	0.062 (0.073)	0.006 (0.075)	0.111 (0.083)	0.172* (0.079)	0.010 (0.081)
Something else	0.678 (0.364)	0.951** (0.360)	0.425 (0.278)	0.719 (0.372)	1.096** (0.382)	0.505 (0.291)
Prefer not to answer	0.224 (0.526)	-0.083 (0.523)	0.582 (0.510)	0.062 (0.585)	0.044 (0.580)	0.575 (0.574)
N(observations)	6,084			5,255		
N(individuals)	1,014			1,014		

Note: Standard errors in parentheses. Table 2 omits the results of participants' age, education, income level, and their prior attitudes toward social equity and social welfares. These omitted values are included in Appendix F. $*p < 0.05; **p < 0.01; ***p < 0.001$.

who identifies as African American with substantial training.

When connecting people's preference choices with their ratings, we find that people rate algorithm reviewers to have a higher level of work efficiency but a lower level of ability to apply equity than bureaucrats. And these findings are not surprising given AI's machine learning-based architecture and, correspondingly, data discrimination (Brundage et al., 2018; Wachter et al., 2020; Young et al., 2019). Hence, when employing AI in the government decision-making process, it would be important to build into the decision-making process values that incorporate equity into its data-driven operation.

For human decision-makers' racial and gender identities, we hypothesized that individuals would have more positive attitudes toward decision-makers who shared the same identities with them. We find partial evidence for this relationship. Indeed, Black participants and female participants are more likely to prefer Black reviewers and female reviewers, respectively. Nevertheless, white participants and male participants do not necessarily have this in-group favoritism. In addition, previous literature suggests that people may prefer automated decision-making when passive representation is not available (Miller & Keiser, 2021). While we find no evidence for this result from our racially minoritized participants, we do learn that, under the circumstance of unavailable representation, African Americans no longer have a strong preference between human and automated decision-makers. These results imply that racially minoritized civilians value government representation and they give preference to those public employees who share their demographic origins and can represent them. This pattern is consistent with passive and symbolic representation studies in the past (Miller & Keiser, 2021; Riccucci et al., 2016; Roch et al., 2018).

These results provide important theoretical implications for the study of representation. This research fills a gap in the representative bureaucracy literature by developing theoretical expectations about the salience of passive representation for Black participants when thinking about public service delivery. These findings raise several new questions for the interaction between automation, representation, and equity. First, when studying frontline worker decision-making, we consistently focus upon the role of race and representation without understanding the underlying mechanism of how representation is salient. When studying decision making if we do not consider the policy context, we can miss the extent to which representation is salient and under what circumstances it matters more to policy implementation. Further, we begin to unpack under what situations automation can be viewed as optimal. This leaves additional questions to discern how or if civilians would still view representation as the most important aspect despite perceived efficiency not being a top priority in the eyes of civilians.

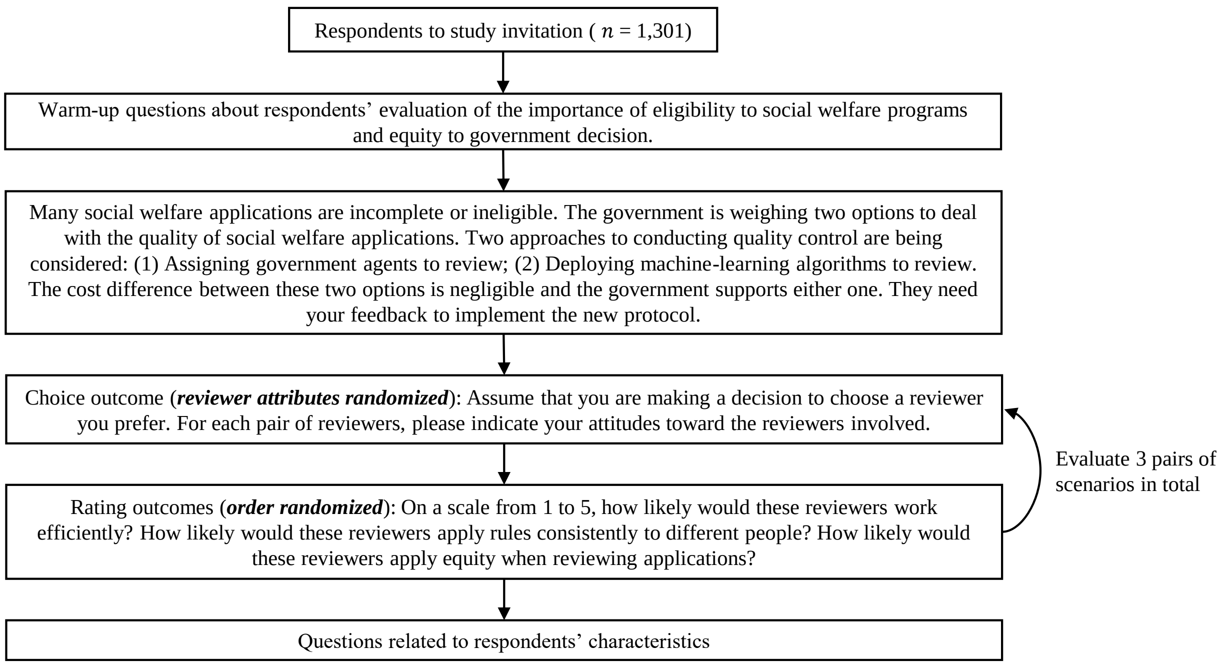
Finally, we investigated the impacts of decision-makers' skill attributes and hypothesized that people would prefer reviewers who had more years of training. Our results support this expectation and show that individuals always choose experienced human reviewers or AI reviewers over their novice counterparts. Civilians' appreciation of training experience has important practical implications for both human resource management and the adoption of algorithms. For the former, it means that maintaining continuous training of current employees and strengthening new employees' training can substantially attract residents' favors. When recruiting a diverse body of public servants to improve representation is challenging, public organizations may choose to focus more on current personnel's training. For the employment of algorithms in government decision-making, using the most advanced technology is likely to have a backfire effect. A more tuned automated decision-making system with extra years of data feeding and training seems to be a safer choice in the civilians' eyes.

There are several limitations worth noting in our study. First, our experiment did not oversample all racially minoritized individuals so that some subgroups have relatively small sample sizes. Accordingly, the experimental results are mainly based on Black and white participants who are males and females. A future study oversampling other racially minoritized groups would be a good way to verify and extend our findings. Second, our design involves a hypothetical situation that asks participants to indicate their preferences. Although the conjoint experiment has unique properties of reducing social desirability bias and simulating real-world decision-making by presenting various attributes jointly to participants (Hainmueller et al., 2014), people's evaluation and preference, in reality, can be also contingent upon whether the reviewer's decision is a positive or negative outcome, how they interact with human or AI reviewers, and various other factors. Therefore, future research using field experiments or evaluating real program performance would be valuable to test our results.

Despite these limitations, our study provides important insights into the application of algorithms to make automated decisions in the government. Scholars and practitioners in public administration have been working on improving organizational efficiency by, for example, reforming service delivery and adopting new technologies. Meanwhile, social equity has become the third pillar for public administration (Frederickson, 1990) and better representation in public organizations has been found as a useful means of promoting improved service quality. Given that AI is expected to serve as a complement to, if not a substitute for, human expertise in the long run, this study points to potential directions for future research and theoretical development to preserve the value of equity in the process of pursuing government efficiency.

Appendix

A Experimental Setup



B Participants' Characteristics ($n = 1,014$)

Characteristic	Frequency	Percent	Characteristic	Frequency	Percent
Gender			Party		
Female	402	39.64	Democrat	407	40.14
Male	601	59.27	Independent	167	16.47
Transgender	7	0.69	Republican	419	41.32
Prefer not to answer	4	0.39	Something else	13	1.28
Race			Prefer not to answer	8	0.79
American Indian or Alaska Native	27	2.66	Ideology		
Asian or Pacific Islander	70	6.90	Strongly conservative	181	17.85
Black or African American	227	23.39	Moderately conservative	188	18.54
Caucasian	609	60.06	Neutral	200	19.72
Hispanic or Latino	42	4.14	Moderately liberal	217	21.40
Mixed racial background	24	2.37	Strongly liberal	218	21.50
Prefer not to answer	15	1.48	Prefer not to answer	10	0.99
Age			Education		
18 to 24	62	6.11	Less than high school	3	0.30
25 to 34	409	40.34	High school or equivalent	72	7.10
35 to 44	286	28.21	Some college but no degree	110	10.85
45 to 54	145	14.30	Associate degree	95	9.37
55 and over	105	10.36	Bachelor's degree or higher	724	71.40
Prefer not to answer	7	0.69	Prefer not to answer	10	0.99
Incomes					
Less than $25,000	113	11.14	$75,000 to 99,999	169	16.67
$25,000 to 49,999	257	25.35	$100,000 and greater	128	12.62
$50,000 to 74,999	333	32.84	Prefer not to answer	14	1.38

C Pooled AMCE Results

Attribute	Result
Reviewer (Baseline: Algorithm)	
Government agent	0.099***
	(0.026)
Reviewer Race (Baseline: African American)	
Caucasian	−0.036
	(0.019)
Hispanic	−0.051**
	(0.018)
Reviewer Gender (Baseline: Female)	
Male	−0.041**
	(0.015)
Year of Training (Baseline: Less than 1-year of training)	
1-4 years of training	0.160***
	(0.015)
5-6 years of training	0.299***
	(0.017)
N(observations)	6,084
N(individuals)	1,014

Note: Standard errors in parentheses. $*p < 0.05; **p < 0.01; ***p < 0.001$.

D Heterogeneous Treatment Effects

Attribute	Race of Respondent			Gender of Respondent		
	Black ($n = 227$)	Caucasian ($n = 609$)	Other Race ($n = 178$)	Male ($n = 601$)	Female ($n = 402$)	Other Gender ($n = 11$)
Reviewer (Baseline: Algorithm)						
Government agent	0.158**	0.117***	0.050	0.084*	0.120**	0.157
	(0.053)	(0.034)	(0.066)	(0.033)	(0.044)	(0.273)
Reviewer Race (Baseline: African American)						
Caucasian	0.108**	0.021	0.016	0.044	0.021	0.316
	(0.041)	(0.024)	(0.043)	(0.024)	(0.030)	(0.249)
Hispanic	0.147***	0.041	0.027	0.057*	0.043	0.152
	(0.040)	(0.023)	(0.040)	(0.023)	(0.029)	(0.222)
Reviewer Gender (Baseline: Female)						
Male	0.017	0.058**	0.007	0.011	0.080***	0.212
	(0.034)	(0.020)	(0.035)	(0.020)	(0.024)	(0.148)
Year of Training (Baseline: Less than 1-year of training)						
1-4 years of training	0.113***	0.170***	0.180***	0.146***	0.180***	0.175
	(0.034)	(0.020)	(0.035)	(0.019)	(0.026)	(0.111)
5-6 years of training	0.109**	0.349***	0.362***	0.135***	0.329***	0.310***
	(0.036)	(0.022)	(0.038)	(0.021)	(0.028)	(0.091)
N(observations)	6,084					
N(individuals)	1,014					

Note: American Indian, Asian, Hispanic, mixed racial background, transgender, and those who preferred not to indicate their racial or gender identities are classified into the "Other" categories for their small sample sizes. Standard errors in parentheses. $*p < 0.05; **p < 0.01; ***p < 0.001$.

E AMCE Results of Minority Subjects Choosing between Bureaucrat and AI

Attribute	Black Participants		Female Participants	
	Black vs. algorithm reviewers	Non-Black vs. algorithm reviewers	Female vs. algorithm reviewers	Male vs. algorithm reviewers
Reviewer (Baseline: Algorithm)				
Government agent	0.301*	0.079	0.120	0.102
	(0.143)	(0.106)	(0.096)	(0.110)
Reviewer Race (Baseline: African American)				
Caucasian	NA	NA	0.103	0.020
			(0.092)	(0.108)
Hispanic	NA	NA	0.069	0.019
			(0.101)	(0.106)
Reviewer Gender (Baseline: Female)				
Male	0.143	0.025	NA	NA
	(0.138)	(0.097)		
Year of Training (Baseline: Less than 1-year of training)				
1-4 years of training	0.016	0.226**	0.088	0.080
	(0.113)	(0.086)	(0.072)	(0.070)
5-6 years of training	0.118	0.144	0.168*	0.129
	(0.126)	(0.085)	(0.072)	(0.071)
N(observations)	124	210	308	290
N(individuals)	56	86	135	134

Note: Standard errors in parentheses. $*p < 0.05; **p < 0.01; ***p < 0.001$.

F Logistic Regression Full Results

Attributes	Algorithm vs. Government Agent			Within Government Agents		
	Efficiency	Consistency	Equity	Efficiency	Consistency	Equity
Reviewer (Baseline = Algorithm)						
Government agent	0.229*	0.013	0.331***	NA	NA	NA
	(0.097)	(0.089)	(0.087)			
Reviewer Race (Baseline = African American)						
Caucasian	NA	NA	NA	0.003	0.048	0.173*
				(0.085)	(0.083)	(0.083)
Hispanic	NA	NA	NA	0.061	0.196*	0.059
				(0.084)	(0.081)	(0.084)
Reviewer Gender (Baseline = Female)						
Male	NA	NA	NA	0.090	0.026	0.112
				(0.069)	(0.067)	(0.068)
Year of Training (Baseline = Less than 1-year of training)						
1-4 years of training	0.623***	0.433***	0.252***	0.646***	0.474***	0.288***
	(0.078)	(0.075)	(0.076)	(0.083)	(0.081)	(0.083)
5-6 years of training	0.737***	0.494***	0.333***	0.763***	0.505***	0.354***
	(0.078)	(0.075)	(0.076)	(0.084)	(0.080)	(0.082)
Race (Baseline = Caucasian)						
American Indian or Alaska Native	0.083	0.393	0.395	0.106	0.395	0.316
	(0.204)	(0.204)	(0.209)	(0.216)	(0.216)	(0.220)
Asian or Pacific Islander	0.591***	0.556***	0.624***	0.668***	0.580***	0.745***
	(0.122)	(0.118)	(0.118)	(0.130)	(0.127)	(0.127)
Black or African American	0.177	0.155	0.063	0.181	0.157	0.034
	(0.090)	(0.086)	(0.086)	(0.098)	(0.093)	(0.094)
Hispanic or Latino	0.402*	0.066	0.265	0.312	0.006	0.121
	(0.178)	(0.158)	(0.167)	(0.185)	(0.167)	(0.175)
Mixed racial background	0.468*	0.233	0.214	0.641**	0.366	0.378
	(0.201)	(0.202)	(0.201)	(0.212)	(0.215)	(0.215)
Prefer not to answer	1.043***	0.977 ***	0.928**	1.050**	1.042**	0.942**
	(0.300)	(0.296)	(0.300)	(0.320)	(0.315)	(0.323)
Gender (Baseline = Female)						
Male	0.083	0.132*	0.042	0.133	0.189**	0.094
	(0.069)	(0.066)	(0.067)	(0.074)	(0.071)	(0.073)
Transgender	0.766	0.557	0.905	0.419	0.567	0.998
	(0.769)	(0.651)	(0.650)	(0.792)	(0.788)	(0.788)
Prefer not to answer	0.606	0.773	0.867	0.500	0.684	1.336
	(0.715)	(0.633)	(0.722)	(0.785)	(0.677)	(0.836)
Age (Baseline =18 to 24)						
25 to 34	0.038	0.007	0.048	0.036	0.066	0.030
	(0.142)	(0.134)	(0.137)	(0.149)	(0.141)	(0.146)
35 to 44	0.037	0.177	0.066	0.094	0.253	0.092
	(0.149)	(0.141)	(0.143)	(0.156)	(0.149)	(0.153)
45 to 54	0.023	0.0126	0.028	0.034	0.090	0.001
	(0.161)	(0.152)	(0.154)	(0.169)	(0.161)	(0.165)
55 and over	0.118	0.077	0.158	0.087	0.212	0.264
	(0.168)	(0.161)	(0.166)	(0.180)	(0.172)	(0.180)
Prefer not to answer	1.401*	1.055	1.913**	1.949**	1.141	2.374**
	(0.644)	(0.609)	(0.667)	(0.743)	(0.666)	(0.784)
Party (Baseline = Democrat)						
Independent	0.202*	0.167	0.337***	0.222*	0.130	0.302**
	(0.095)	(0.090)	(0.091)	(0.101)	(0.097)	(0.100)

Republican	0.059 (0.077)	0.062 (0.073)	0.006 (0.075)	0.111 (0.083)	0.172* (0.079)	0.010 (0.081)
Something else	0.678 (0.364)	0.951** (0.360)	0.425 (0.278)	0.719 (0.372)	1.096** (0.382)	0.505 (0.291)
Prefer not to answer	0.224 (0.526)	0.083 (0.523)	0.582 (0.510)	0.062 (0.585)	0.044 (0.580)	0.575 (0.574)
Education (Baseline = Less than high school)						
High school or equivalent	0.393 (0.525)	0.714 (0.539)	0.124 (0.526)	0.502 (0.555)	0.807 (0.580)	0.053 (0.563)
Some college but no degree	0.577 (0.521)	0.213 (0.536)	0.346 (0.523)	0.637 (0.550)	0.306 (0.578)	0.289 (0.560)
Associate degree	1.013 (0.524)	0.045 (0.538)	0.608 (0.525)	0.820* (0.544)	0.039 (0.581)	0.683 (0.563)
Bachelor's degree or higher	0.719 (0.515)	0.045 (0.531)	0.541 (0.517)	1.257 (0.799)	0.122 (0.572)	0.519 (0.553)
Prefer not to answer	0.972 (0.728)	0.507 (0.743)	0.940 (0.733)	0.002 (0.127)	0.529 (0.815)	1.057 (0.814)
Incomes (Baseline = Less than $24,999)						
$25,000 to 49,999	0.034 (0.119)	0.090 (0.114)	0.333** (0.118)	0.002 (0.127)	0.126 (0.123)	0.389** (0.129)
$50,000 to 74,999	0.210 (0.117)	0.163 (0.113)	0.303* (0.118)	0.151 (0.124)	0.145 (0.122)	0.366** (0.129)
$75,000 to 99,999	0.198 (0.131)	0.134 (0.123)	0.226 (0.128)	0.193 (0.138)	0.162 (0.132)	0.218 (0.140)
$100,000 and greater	0.090 (0.139)	0.049 (0.134)	0.261 (0.137)	0.124 (0.148)	0.007 (0.144)	0.270 (0.150)
Prefer not to answer	0.371 (0.411)	0.379 (0.358)	0.324 (0.416)	0.555 (0.442)	0.330 (0.382)	0.283 (0.446)
Social welfare eligibility (Baseline = Strongly disagree)						
Somewhat disagree	1.063*** (0.269)	0.526* (0.250)	0.543* (0.248)	1.332*** (0.308)	0.617* (0.274)	0.388 (0.268)
Disagree	0.664* (0.305)	0.471 (0.284)	0.381 (0.281)	0.923** (0.343)	0.611* (0.310)	0.195 (0.304)
Neither agree nor disagree	0.946*** (0.266)	0.365 (0.246)	0.316 (0.244)	1.239*** (0.304)	0.417 (0.271)	0.195 (0.264)
Agree	0.147 (0.254)	0.530* (0.233)	0.575* (0.231)	0.110* (0.293)	0.503 (0.257)	0.738** (0.250)
Somewhat agree	0.379 (0.257)	0.209 (0.237)	0.228 (0.235)	0.674 (0.296)	0.080 (0.261)	0.327 (0.255)
Strongly agree	0.016 (0.254)	0.524* (0.234)	0.618** (0.232)	0.388 (0.293)	0.366 (0.257)	0.675** (0.251)
Social equity priority (Baseline = Strongly disagree)						
Somewhat disagree	0.036 (0.234)	0.053 (0.227)	0.217 (0.227)	0.052 (0.253)	0.112 (0.245)	0.002 (0.244)
Disagree	0.144 (0.244)	0.179 (0.238)	0.094 (0.236)	0.054 (0.263)	0.099 (0.255)	0.106 (0.253)
Neither agree nor disagree	0.290 (0.225)	0.031 (0.218)	0.159 (0.216)	0.249 (0.241)	0.025 (0.233)	0.078 (0.232)
Agree	1.124*** (0.221)	0.872*** (0.214)	0.965*** (0.212)	1.042*** (0.236)	0.777*** (0.228)	0.749*** (0.227)
Somewhat agree	0.591** (0.220)	0.465* (0.213)	0.486* (0.211)	0.536* (0.235)	0.413 (0.228)	0.293 (0.226)

Strongly agree	0.992***	0.708***	0.885***	0.963***	0.674***	0.695**
	(0.221)	(0.213)	(0.212)	(0.236)	(0.228)	(0.227)
Intercept	0.106	0.200	0.418	0.130	0.436	0.170
	(0.593)	(0.601)	(0.589)	(0.633)	(0.647)	(0.630)
N(observations)	6,084			5,255		
N(individuals)	1,014			1,014		

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