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Bureaucrat or Artificial Intelligence: People's Preferences and Perceptions of Government Service*

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Abstract

The increasing use of artificial intelligence (AI) in public service delivery presents important yet unanswered questions about citizens' views of AI. Are citizens' perceptions of decisions made by AI different from those made by bureaucrats? We answer this question by conducting a conjoint experiment. Our results show that individuals prefer minority bureaucrats over AI to make decisions. This is particularly true for racially minoritized citizens. However, when passive representation within the bureaucracy is unavailable, 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.

Keywords: artificial intelligence, government service, administrative decision-making, discretion, representation, representative bureaucracy, equity

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1 Introduction

Traditional public administration decisions have consisted of a public servant interacting with a citizen[1] to determine the correct legal course of action for the citizen. However, there has been a recent push to use artificial intelligence (AI) and algorithms[2] to help facilitate public decision-making and service delivery. This is an initiative that began in the early 1990s and 2000s with public organizations using advanced information technology to help them make better decisions in public service delivery, such as predictive traffic congestion and COMPSTAT (Tong & Wong, 2000; Walsh, 2001). As part of this push for increased automation, scholars argue that AI-powered automation can further increase organizational performance and efficiency in administrative decision-making (Zekić-Sušac et al., 2021). Moreover, scholars argue that the use of digital technologies 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, a branch of AI that focuses on data and algorithms to emulate human learning, to provide image or handwriting recognition (IBM Cloud Education, 2020), which is then used to create chains of automation for straightforward tasks (Veale & Brass, 2019). A second example that has become more prevalent in public service is the use of automated call centers where AI is used to search documents and help agents to solve customer inquiries (Mehr, 2017).

There is also a growing movement associated with trustworthiness in AI that has partly attributed to the uptick of AI in public service. The concept dubbed "trustworthy AI (TAI)" is predicated on the notion that buy-in and trust from individuals and organizations to use AI is predicated on AI being designed with transparency, tangibility, and reliability as its hallmarks (Glikson & Woolley, 2020; Medaglia et al., 2021; Thiebes et al., 2021). Similarly, European Commission proposes that trust in AI is achieved by four principles, i.e., having respect for human decision-making, fairness, preventing harm to others, and solvable solutions (Braun et al., 2021). When AI is trustworthy, individuals will follow the system's solutions or recommendations. This indicates the need for AI to be trustworthy so that there can be path dependency between the AI setting forth the recommendation and the individual or group following that recommendation (Aoki, 2020).

With scholars paying particular attention to trustworthiness in AI, there has been an increase in AI usage in public administration. For example, applications for government programs (such as unemployment benefits), government services (such as trash pick-up and pothole repair), and requiring permits have moved to e-platforms that adopt AI (Gil et al., 2019). In the case of social welfare, when individuals fill out application forms electronically, there could be two systems behind a computer screen to review applicants and applications: bureaucrats and algorithms. In some cases, algorithms start to work before a human decision-maker steps in—to search multiple databases and 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). In this regard, understanding how it shapes equity in outcomes and representation has

[1] We use the term *citizen* to identify individuals affected by public employees' decisions, rather than a specific legal status of citizenship (Roberts, 2021).

[2] 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, such as imitating human intelligence (Merriam-Webster, 2021a). In this paper, for the sake of readability, we use artificial intelligence (AI) and algorithms interchangeably. Similar usage is commonly seen, e.g., algorithm appreciation and aversion (Dietvorst et al., 2015; Logg et al., 2019).

also become an important aspect, which has not been extensively studied.

Recent literature has started studying the relationship between automated decisions without AI and the role of representation (representative bureaucracy) and found that traditional under-resourced communities prefer automation using basic logic models but only in a traditionally antagonistic public profession (policing), between communities of color and public service (Miller & Keiser, 2021). However, automation is such an expansive field that even less is known about the sub-disciplines it has created. To add to what we know about representative bureaucracy, in particular symbolic representation, there is a growing need for research in different policy areas outside of policing. Given that automation with AI, as another form of automation that does not follow the preprogrammed if-then logic to make decisions, would be far more intelligent (Gaynor, 2020; Medaglia et al., 2021), understanding who benefits the most from AI-driven automation and if efficiency *and* equity can co-exist in multiple public services areas is equally, if not more, important.

With this in mind, we conducted a conjoint experiment in which participants weighed two options to deal with the quality of social welfare applications, namely assigning bureaucrats or AI reviewers to examine applicant eligibility and application completion. We randomized a 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 all respondents regardless of their race 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 may regard other bureaucrats and AI the same. In addition, we find that people believe that AI is more efficient than bureaucrats, but less capable of applying equity. These findings add to the symbolic representation literature, with its exploration comparing representation with automation. Our paper contributes in two ways. First, it introduces a new policy area with important salience for citizen-state interactions (welfare). Second, these results are the first to indicate that for Black individuals' representation is most salient for issues of equity and efficiency only when the government agent shares the same racial identity.

2 Literature Review

AI technologies are widely employed in today's world, ranging from chatbots using natural language processing, algorithm-driven marketing, medical image analysis, to financial modeling, and supervising services involving facial recognition (Bughin et al., 2017; Jordan & Mitchell, 2015). In the public sector, AI meets the needs of smart government to interact with citizens who spend more and more time living and working in the digital realm, allowing public organizations to better understand their citizens and clients (Margetts & Dorobantu, 2019; Vogl et al., 2020). Therefore, AI has been used in social welfare programs to determine eligibility (Martinho-Truswell, 2018), in courtrooms to predict recidivism (Van Dam, 2019), and in university admissions to predict student performance (Moody, 2020). Depending on contexts and tasks, AI is complementing, supplanting, or cooperating with human capabilities to make government decisions.

While the use of AI is expanding, 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, 2021; 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, 2021) and favoritism or unfairness due to algorithm manipulation ((L. Andrews, 2019). Still, it is largely unclear how citizens understand and respond to the escalating involvement of AI in the government (Sharma et al., 2020). Particularly, do people perceive government services provided by AI differently from those provided by bureaucrats? Do they prefer AI or bureaucrats to make decisions in government service? These questions are critical to public managers because the answers may directly suggest what areas public organizations can leverage AI and what areas they still need humans to foster people's trust in the government (Ariely, 2013; Chingos, 2012). Successful government service needs these answers as citizens' positive perceptions cultivate public trust and satisfaction, leading to a higher willingness to engage in coproduction and compliance with future policies among citizens (Hibbing & Theiss-Morse, 2001; Im et al., 2014).

Many factors influence individuals' attitudes toward the government and its service provider. Studies have found that people's attitudes may be positively associated with better performance outcomes (Aytaç, 2021; Porumbescu et al., 2019), which can be affected by training and personnel management. Dermol and Čater (2013) argue that years of training make public servants more professional, leading to better performance outcomes. For AI agents, more time invested in improving data quality, adjusting algorithms, and testing models is a general way to improve their performance (Glikson & Woolley, 2020; Zewe, 2022). Nevertheless, actual performance is not necessarily equal to perceived performance due to people's differing needs for public service and understanding of service performance (Bansal et al., 2021; Van de Walle & Bouckaert, 2003). Studies on citizen-state interaction and TAI suggest that people's views are also associated with performance information (James & Moseley, 2014; Porumbescu et al., 2021), the administrative process concerning transparency and justice (Grimmelikhuijsen, 2010; Van Ryzin, 2015), and autonomy (Song et al., 2021; Thiebes et al., 2021). Moreover, a feeling of representation and empathy can affect people's attitudes toward the government and its service providers. For this reason, researchers have found that representative bureaucrats and anthropomorphic AI are more likely to gain people's trust and facilitate positive citizen-government interactions (Glikson & Woolley, 2020; Pelau et al., 2021; Van Ryzin et al., 2017).

2.1 Attitudes Toward Government through A Representation Lens

Representative bureaucracy theory argues that the citizen-state interaction may benefit from shared demographic and social characteristics between bureaucracies and the public (Bishu & Kennedy, 2020). When the bureaucracy's workforce has similar demographic and socioeconomic compositions to the constituent populations it serves, this is known as passive representation (Mosher, 1968). In the decision-making process, bureaucrats may use their administrative discretion on a basis of their favored passive representation, a moment in which active representation manifests and benefits the represented social group (Bradbury & Kellough, 2007; Meier, 1975). Recent studies further investigate the connection between representation and citizen perception of government service, pointing out that a symbolically representative bureaucracy per se may create a feeling of commonality and influence people's attitudes (Riccucci et al., 2016; Roch et al., 2018; Theobald & Haider-Markel, 2008).

According to symbolic representation, without any changes in policy or affirmative steps made by bureaucracies, citizens may improve their view of fairness, trustworthiness, legitimacy, and perceived performance in government if they see matched social origins from the bureaucrats they are interacting with (Gade & Wilkins, 2013; Scherer & Curry, 2010). Some researchers find that symbolic representation can enhance people's perception of government even when the administrative outcome is unfavorable (Roch et al., 2018). Positive examples like this have important implications for policy implementation, encouraging individuals to cooperate, comply with government decisions, and coproduce desired policy outcomes (Hurwitz & Peffley, 2005; Riccucci & Van Ryzin, 2017).

Two types of social origins have been primarily examined in the research of symbolic representation, namely race and gender, partially because they are the most salient characteristics in the United States to influence administrative behaviors and individual perceptions (Kennedy 2014). For race representation, race-matching teachers may improve both parents' and students' perceptions of school discipline as well as the fairness and legitimacy of bureaucratic behavior (Roch et al., 2018). In a policing scenario, citizens are more likely to see police activities as legitimate when they see police officers from their racial group present (Theobald & Haider-Markel, 2008). Also looking into people's evaluations of police service, Riccucci et al. (2018) find that race representation can significantly affect people's evaluations of performance, trustworthiness, and fairness. For Black citizens, 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 faces more complaints about police misconduct and has worse performance.

Similarly, studies find positive impacts of gender representation and congruence on people's attitudes toward government service (Baniamin & Jamil, 2021; Meier & Nicholson-Crotty, 2006; Riccucci et al., 2014). For example, female police officers are more willing to support and actively represent women in terms of domestic violence (R. Andrews & Miller, 2013). Relatedly, female victims are also more likely to report sexual assault when facing female police officers (Meier & Nicholson-Crotty, 2006). A potential explanation for this positive association is that female victims may perceive gender-incongruent officers as less receptive and empathetic, deterring them from reporting crimes. In a recent study situated in a scenario of sexual harassment complication, female complainants are found to prefer female mediators and rate their performance at a higher level (Hibbard et al., 2022). These empirical studies indicate that better gender representation improves people's perceived job performance, trustworthiness, and fairness, increasing citizens' willingness to coproduce and comply (Baniamin & Jamil, 2021; Riccucci et al., 2014).

Many pieces of research have supported that racial and gender congruence between citizens and bureaucrats can lead to citizens having more favorable attitudes toward government service. However, a large portion of them concentrates on the fields of policing and education where race and gender are salient enough to affect individuals' perceptions (Cochran & Warren, 2012; Hilliard & Liben, 2010). On the other hand, the effects of symbolic representation are inconclusive as its influences on people's attitudes vary by service area (Lee & Nicholson-Crotty, 2022). To address this issue, this study situates itself in a scenario in which bureaucrats make low-stakes, instead of urgent or significant, decisions for citizens so that race and gender are less salient. We hypothesize that citizens in this situation have a choice of whom they would like to interact with:

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

2.2 Lack of Representation: Out-group Bureaucrats and AI

Existing literature further looks into reverse representation, which occurs when citizens and government agents do not share commonalities (McLaughlin et al., 2021). In a police search context, Theobald and Haider-Markel (2008) find that Black citizens are less likely to regard White officers' activities as legitimate, whereas White citizens are less likely to view Black officers' actions as legitimate. Their results suggest that people may have negative perceptions of government agents due to a lack of symbolic representation. Only when individuals see a symbolic representation of themselves, may they be more open to opportunities for positive engagements with government service (Riccucci et al., 2018). Otherwise, White citizens will respond to greater Black representation in a police department with increased negative attitudes toward the agency's performance and trustworthiness. And Black citizens' perceptions of job performance, trust, and fairness may decrease in the case of greater White representation.

However, some scholars argue that privileged individuals in terms of social origins may be less concerned about the lack of representation (McIntosh, 1998; Miller & Keiser, 2021). Some empirical evidence supports this claim. As mentioned above, Black citizens' perception of police fairness varies substantially with police representativeness. In contrast, White citizens do not worry about police officers' fairness even though there is a greater representation of Black officers (Riccucci et al., 2018). Regarding gender representation, there is also an asymmetry that both women and men care more about women being underrepresented compared to men being underrepresented (Block et al., 2019). Different treatments that Whites and males receive in daily life, as compared to non-White individuals and females, may contribute to the disparity in their concerns about representation. An example is that Black civilians may be subject to more force when facing White officers, whereas a racial mismatch between White civilians and Black officers does not increase the level of the police force (Wright & Headley, 2020). For privileged individuals, the advantages of dominating social construction offset the disadvantages of missing symbolic representation at a certain point of government service delivery. Presumably, minorities would care more about representation and have a strong preference for those who can represent them over those who cannot.

Having said that, minority citizens regularly interact with government services in which they have no passive representation and perceive no symbolic representation. Therefore, when replacing bureaucrats with AI agents in government decision-making and service delivery, this replacement does not necessarily worsen minority citizens given that AI is another decision-maker that lacks passive representation (Miller & Keiser, 2021). To be specific, people tend to perceive technology as cold and inhuman (McFarland, 2015; Pols & Moser, 2009). While AI technologies appear in the real world in a variety of ways, including physical robots, virtual assistants, and embedded functions, these manifestations many times do not involve visualization, anthropomorphism, or social identities that human beings could connect with (Glikson & Woolley, 2020). The absence of commonality prevents AI from representing people and alienates their trust in AI.

However, as the rose-colored glasses of representation fade when it compares AI with out-group bureaucrats, minority citizens' preferences now would be closely associated with their understanding of how AI and out-group bureaucrats exercise discretion and make decisions. Regarding this, we hypothesize:

H2: Minorities will have more positive attitudes toward AI when bureaucrats do not share the same racial or gender identities with them.

This hypothesis is based on two underlying assumptions (1) that bureaucratic discretion and AI are different, and (2) that people can perceive those differences and do have a preference. We will discuss the first assumption in the next section and focus on the second one here. Prior research documents an algorithm appreciation phenomenon that laymen prefer algorithmic to human decisions (Logg et al., 2019; Thurman et al., 2019). In other words, decisions made automatically by AI are frequently regarded as equal to or even better than those made by human professionals. However, the argument for algorithm appreciation has mixed results and is not yet conclusive. For example, Miller and Keiser (2021) discover that, in the case of traffic violation ticketing, Black citizens, but not White citizens, are more likely to perceive AI better than police officers. In addition, algorithm appreciation may be limited to the scenarios in which crucial decisions are involved, such as those concerning safety, healthcare, and justice. People do not seem to have a strong preference when human beings and AI are making trivial decisions (Araujo et al., 2020). Furthermore, and quite the opposite, participants in some studies may constantly display a pattern of being averse to AI even if they know AI outperforms human (Burton et al., 2020; Dietvorst et al., 2015). To this end, we develop *H2* to investigate people's preferences in certain conditions.

2.3 Bureaucrats vs. AI: A Comparison in Efficiency, Consistency, and Equity

Although bureaucrats and AI both work under "rules of law," the ways them making decisions are arguably different. AI systems can process massive amounts of information within seconds and be programmed to preserve public interest (Barth & Arnold, 1999; Chatterjee et al., 2022). This principle requires AI agents to uphold fundamental human rights and promote the welfare of people and the environment (Barth & Arnold, 1999; Toreini et al., 2020). On the other hand, bureaucratic discretion refers to bureaucrats' decision-making flexibility with which government policies are implemented in complex and ambiguous problem environments (Bullock, 2019). Since bureaucrats are motivated by self-interests and are cognitively bounded, bureaucratic discretion can possibly involve discretionary abuse, personal bias, and administrative errors (Battaglio et al., 2019; Prendergast, 2007; Simon, 1947). Even if improving bureaucrats' professionalism and representation may reduce the likelihood of these events (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, the use of AI in government service has some key assets in terms of efficiency, consistency, and equity that help address problems in bureaucratic discretion and general administrative decision-making (Young et al., 2019).

For many public organizations, inefficiency is the key obstacle to performance improvement. Bureaucratic inefficiencies include unnecessary paperwork, administrative delays, and human errors, which the use of AI could instrumentally help alleviate (Ingrams et al., 2022). Pandey and Bretschneider (1997) predict that if the communication process is streamlined, many of the negative effects of red tape would vanish as they believe information and communications technology can be used to contain red tape. This argument is later supported by Welch and Pandey (2006), whose study identifies that a higher level of intranet implementation by public organizations is associated with lower perceived levels of red tape because of the instrumental advantages in terms of speed and efficiency. When it comes to AI in particular, it has good scalability that can easily outpace human capacity for processing information and managing workload (Alexopoulos et al., 2019; 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 during 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). Because of its machine learning-based architecture, AI systems are scalable and exploit information much faster than human capacity, increasing government operation efficiency by improving per-task speed and completing more tasks with lower marginal costs (Bullock, 2019; Ojo et al., 2019; Young et al., 2019). As a result, higher efficiency achieved by AI may improve citizens' perceptions of government service (Kuziemski & Misuraca, 2020; Welch & Pandey, 2006).

Relatedly, scalable AI can provide better decision reliability or consistency than bureaucratic discretion, which is an important perspective in shaping citizens' perceptions of trustworthiness (Toreini et al., 2020). Particularly, the reliability and consistency of AI are positively associated with people's acceptance (Glikson & Woolley, 2020). Compared to bureaucrats' decision criteria that may change from one agent to another, vary across different times, and even depend on various moods (Andersen & Guul, 2019; Eren & Mocan, 2018), using AI technologies to make decisions can prevent bureaucrats' personal factors from influencing the decision-making process and uses one set of algorithms to make decisions consistently and predictably (Mcknight et al., 2011; Young et al., 2019).

The removal of bureaucrats' personal bias has a special implication for minority citizens. 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 citizens may be or may perceive themselves to be placed at a disadvantage in government service and administrative decision-making. From the standpoint of bureaucrats, they may also feel unfamiliar with minority citizens' 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 minority citizens believe that unrepresentative bureaucrats are biased against them, then they are likely to turn to AI for decision-making and service delivery.

With AI being incorporated into government operations, it is important to understand its limitations. For now, there is still a long way to go to realize many magical benefits beyond simple functions outlined by AI advocates as people are still figuring out how to take advantage of AI and when (Hendler, 2020). In comparison to the private sector, there is less understanding of AI's negative implications pertaining to government service and public decision-making (Wirtz et al., 2020; Zuiderwijk et al., 2021). In this regard, a recent publication alerts the public sector of challenges brought by AI, including the exclusion of certain stakeholders, increased complexity, dehumanization of government service, infringement of privacy, technology obedience, as well as new legislative and supervision requirements (Medaglia et al., 2021). In addition, the initial application of AI may have rebound effects on efficiency and consistency as government operations need to adjust to the new technologies (Nishant et al., 2020; van Leeuwen et al., 2022). Meanwhile, the lack of deep technical understanding of AI on the part of policymakers may lead to poorly designed or ill-informed regulatory, legislative, or other policy responses (Brundage et al., 2018), exacerbating AI's negative implications. While there is a growing awareness of AI's weakness in the government and society, AI is increasingly autonomous and invisible, creating a black box in the decision-making process that is hard to be explained or audited (Janssen et al., 2020; Zuiderwijk et al., 2021). Hence, it could be difficult for public organizations to manage and for citizens to understand AI systems in a transparent and accountable manner (Toreini et al., 2020; B. Zhang & Dafoe, 2020).

One of the consequences is that people doubt whether automated decisions can fully respect the values of equity and fairness (Wachter et al., 2021). Their reservations are reasonable when considering AI's data feeding and learning nature. In theory, by relying on statistically fair links between algorithmic inputs and the decision outcome, AI can decrease discrimination and promote equity (Yang & Dobbie, 2020). Yet, human involvement in the development of AI systems can end up creating inequity. System-level bureaucrats may contribute to the architecture and training of algorithms while street-level bureaucrats may produce data for AI to train (Bovens & Zouridis, 2002; Glikson & Woolley, 2020). The choice of using certain characteristics, such as race, gender, and even seemingly neutral trait like education, in AI systems can cause unfair treatment of individuals if these characteristics are correlated with discrimination (Barocas & Selbst, 2016). Furthermore, the data used for training AI have been well-documented skewed and containing 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) administrative decision-making (Young et al., 2019). Based on the discussion above, we hypothesize that:

H3: People are likely to believe, in comparison to bureaucrats, AI to have better performance on efficiency and consistency but worse performance on equity.

3 Method

We implemented 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 were under review for applicant eligibility and application completion. We have two reasons to situate this study in a social welfare context. First, it is traditionally one of the scenarios in which bureaucrats and citizens, especially marginalized citizens, frequently interact with each other (Hasenfeld et al., 1987; Keiser, 1999). Lipsky (1980) named welfare officers as an example of street-level bureaucrats whose discretion occupies an influential position in government service delivery. Second, social welfare is one of the services most likely to be automated by AI as we move forward. Countries like the Netherlands, Denmark, and Australia have employed AI technologies to detect welfare fraud and citizens at risk of neglect (Gantchev, 2019). Such uses have stirred up trust issues and public concerns about social justice, privacy protection, and algorithmic transparency (Mann, 2020). However, the quality review is a tiresome and monotonous task for bureaucrats and a low-stakes decision for citizens as compared to high-impact decisions like police searches.

3.1 Experimental Design

In our conjoint experiment, each respondent 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 years 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 applicable" racial and gender identities. Correspondingly, we ruled out the possibility for government agent reviewers to have "not applicable" attributes. Our subsequent analysis has considered these restrictions.

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

We first asked about participants' existing attitudes toward the importance of eligibility for social welfare programs and the importance of equity in government decisions. Following these 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 reads "[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 instructed to predict three dimensions of reviewers' performance. We measured them to understand whether their predicted reviewers' performance influences their preference decisions. The first dimension focuses 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 reads "how likely would these reviewers apply rules consistently to different people?" and the last question asks, "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)[3] and received approval from the Human Subjects Research Office at Florida State University.[4] We targeted 1,000 U.S. adults administered through Amazon Mechanical Turk (MTurk) in October 2020. 1,301 individuals turned 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, 139 for not completing the survey,[5] and 44 for missing information. After these procedures, 970 respondents became our final sample. Since participants in our conjoint experiment are asked to evaluate three pairs of reviewer profiles, this study obtains 6 observations from each participant and $970 \times 6 = 5,820$ observations in total. We report the descriptive statistics of respondents' characteristics and responses in Appendix B. A typical respondent in our experiment would be a Caucasian male who has a similar chance to be

[3]The pre-registration can be accessed via https://osf.io/mb7u4.

[4]The experiment has been reviewed for any potential harm to human subjects and granted an institutional review board (IRB) "exempt" status (IRB Protocol STUDY00000993).

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

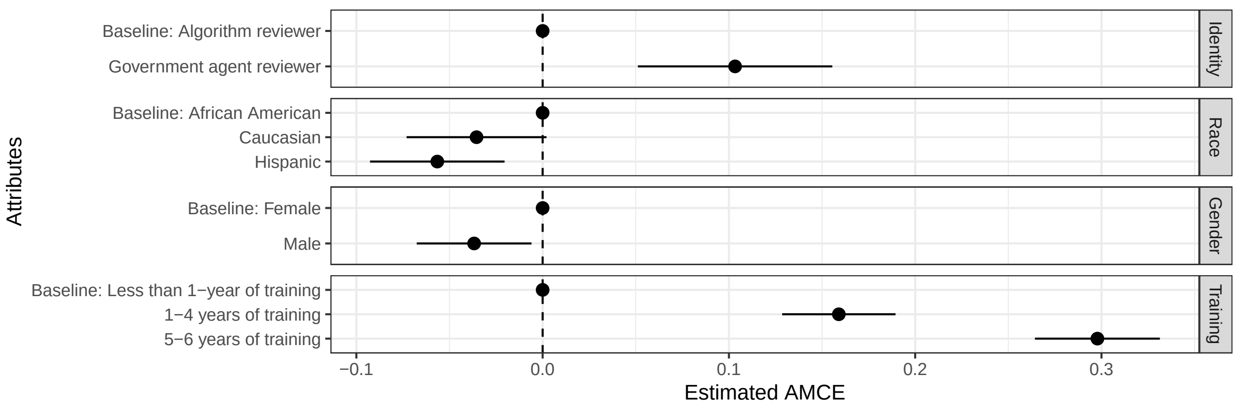
Republican or Democrat and identifies himself as moderately liberal. He has completed at least undergraduate education and has a household income between \$50,000 to \$74,999. With 970 respondents and 0.05 expected effect size, the predicted statistical power for our design is 86%, which is generally acceptable in social sciences (Stefanelli & Lukac, 2020).

4 Analysis and Results

4.1 Conjoint Analysis

Looking into respondents' choice outcomes, we conduct conjoint analysis and estimate each attribute's average marginal component effect (AMCE).[6] 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: 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.

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 citizens' preference of a particular reviewer. A positive AMCE indicates citizens' 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 10.3% ($SE = 0.026$) more likely to choose a government agent rather than an algorithmic agent to review their applications. Regarding reviewers' training background, substantial training provides a bonus. Reviewers who possess 5-6 years of training would be about 29.8% ($SE = 0.017$) more likely to become respondents' preferred reviewer in comparison with baseline reviewers with less than 1 year of training.

[6] 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).

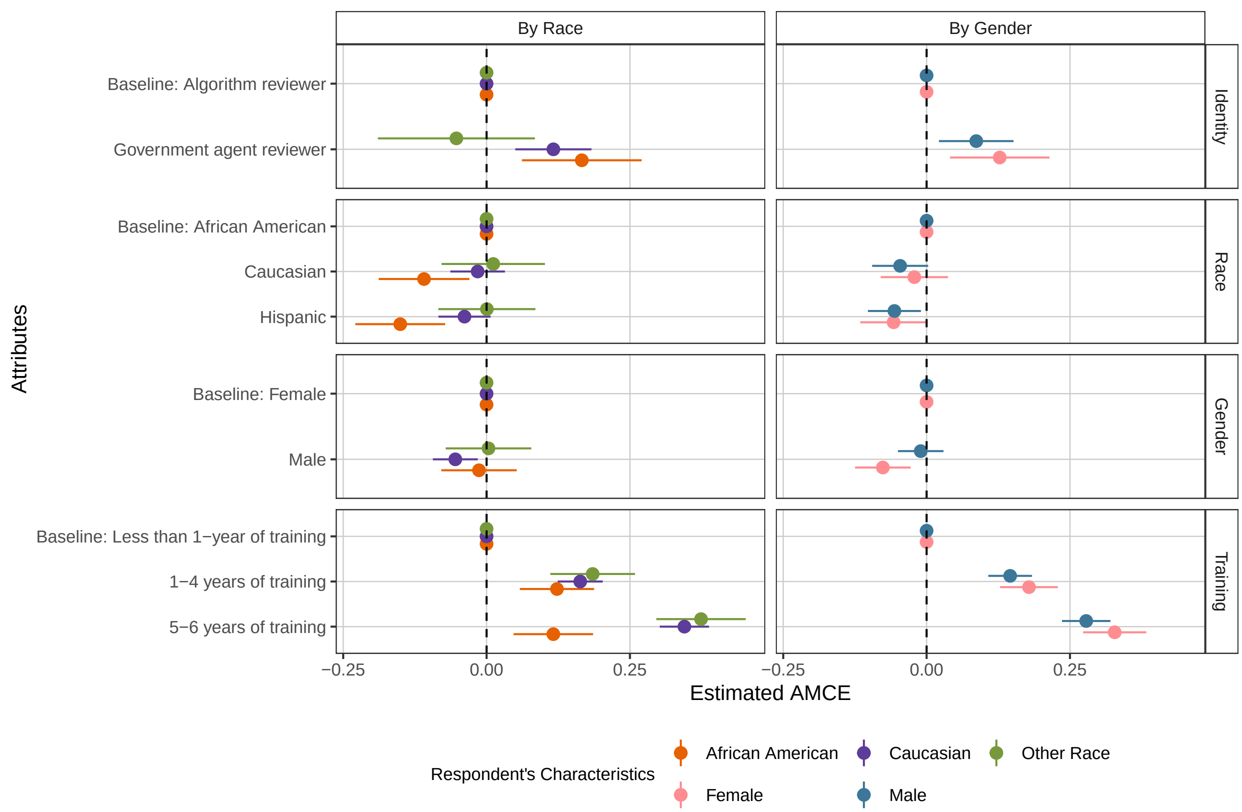
Relatively, 1-4 years of training has a less significant advantage over the baseline, increasing the likelihood by 15.9% ($SE = 0.016$).

Given that we have restrictions to prevent meaningless attribute combinations, we do 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 -0.037 ($SE = 0.016$), suggesting that females are 3.7% more likely to be people's desired reviewers than male bureaucrats. For racial identities, Caucasian and African American reviewers do not have a statistically significant difference while a Hispanic reviewer is 5.7% less likely to be preferred over an African American reviewer ($SE = 0.018$).

4.2 Heterogeneous Effects

In addition to AMCEs, we examine potential heterogeneous treatment effects, which can be caused by the respondents' characteristics. 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. Figure 2 visualizes our results which are reported in Appendix D.

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.

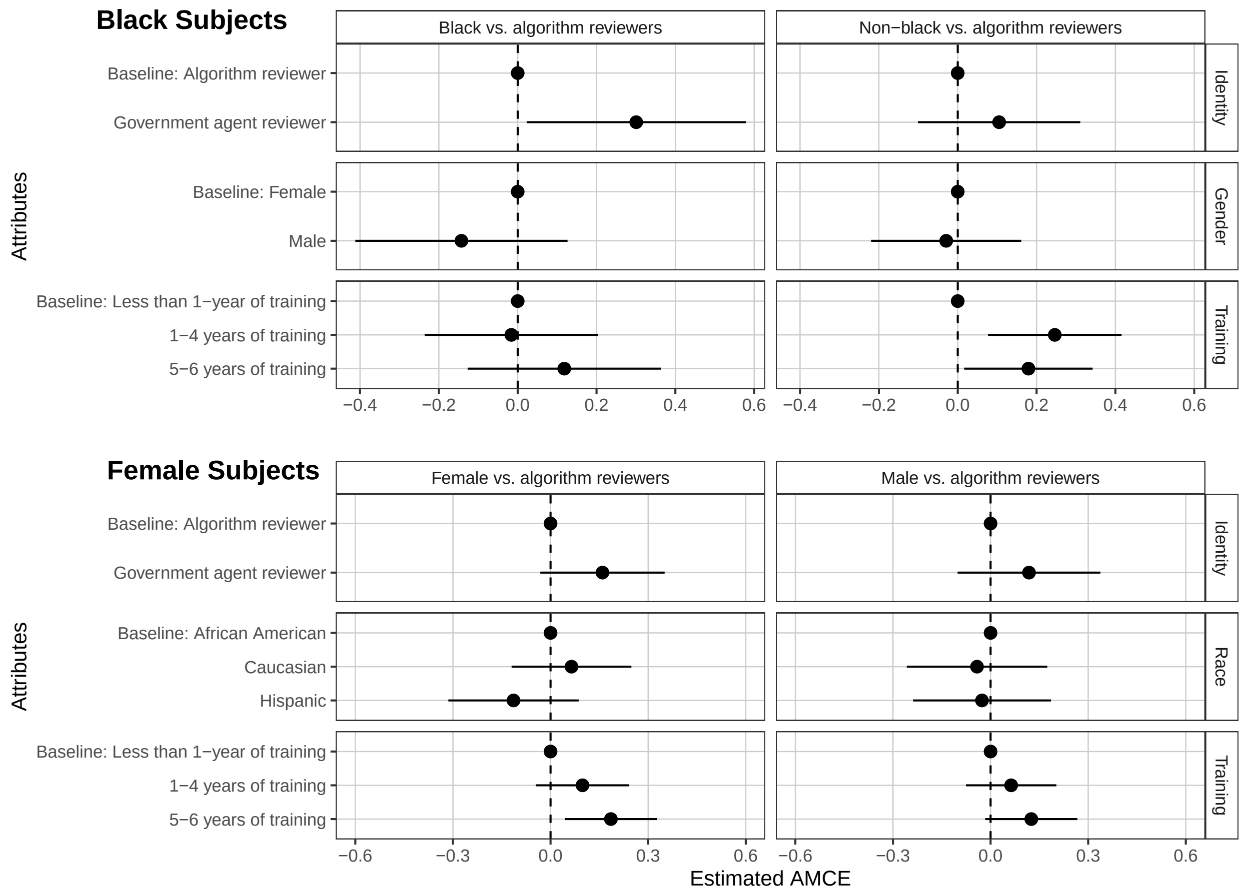
Starting with race, it is worth mentioning that some racial groups in our study have relatively small sample sizes, so we have classified them into the "Other Race" category. The results show that both African American and Caucasian participants have a strong preference for government agents over algorithms. Bureaucrat reviewers would be 16.6% and 11.6%, respectively, more likely to be their reviewers in the quality control process than AI reviewers. Furthermore, African American participants show a strong preference, over 10% more likely, for African American reviewers over other human decision-makers while Caucasian and other race participants do not show similar in-group preferences. As for the reviewer's gender, Caucasian respondents demonstrate a preference for females (5.4% more likely) whereas others do not. The fourth attribute, year of training, is the most regularly used reviewer attribute. Every racial group is disinclined to have a reviewer with little training and most racial groups favor a reviewer with 5-6 years of training. The effects of 5-6 years of training increase the likelihood of being a preferred reviewer by 11.6% to 37.3%.

Then, we investigate the effects of reviewer attributes across respondents' gender. We find a consistent preference for government agent reviewers in both male and female respondents. Moreover, male respondents report a slight reluctance (5.6% less likely) to have a Hispanic reviewer when the alternative could be a Black reviewer. Female subjects take the reviewer's gender into account and prefer female reviewers over males by 7.6%. 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 tend 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 minority citizens care about representation and have a preference for race and gender congruence between reviewers and themselves.

Because of this preference, it is natural to ask what would happen when minority citizens do not have their preferred human decision-maker and whether they would turn to prefer AI. Our *H2* posits that minorities would prefer AI reviewers when the alternative is out-group human agents whose race or gender identity is incongruent with theirs. We test *H2* with a closer look at a subset of observations in which minority respondents choose between a human agent and an AI agent. 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 minority participants' preference choices broken down by whether the government agent reviewer is passively representing the participants. When making these choices, the participants are offered two options: a human decision-maker and an AI reviewer. The left facet shows the results when the government agent reviewer has a matched racial or gender 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 a statistically significant negative difference in minority respondents' preference between incongruent human decision-makers and AI reviewers. Nevertheless, Black participants in the upper panel perceive little difference between out-group bureaucrats and AI taking charge of the decision-making process while they perceive statistically significant differences between in-group bureaucrats and AI. For female participants in the lower panel, they do not pay too much attention to bureaucrats' social origin and regard gender-congruent and -incongruent agents the same when the other option is AI reviewers.

Figure 3: Minority Subjects Choosing between Bureaucrat and AI



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

4.3 Logistic Regression

Lastly, we shift gears to three rating outcomes. Recall that participants were asked to predict human and AI reviewers' work efficiency, consistency, and ability to apply equity on a scale from 1 (extremely unlikely) to 5 (extremely likely). We dichotomize these ratings into 0 (not likely) 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 government agents and algorithm reviewers,

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

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,

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

Since our logistic regression models are a family test regarding respondents' evaluations of efficiency, consistency, and ability to apply equity, we adjust the results' p value by using the Bonferroni correction and establishing the significance level at $(0.1/3) = 0.033$. Table 2 demonstrates the main results. When comparing government agents with algorithm reviewers, human decision-makers are hypothesized in *H3* to perform poorer than AI reviewers in terms of efficiency and consistency but better regarding applying equity. The results find evidence to partially support *H3*. Specifically, AI is rated to be lower in equity than government agents to a statistically significant level. Put differently, according to our respondents' prediction, government agent reviewers have 38% more odds of having the ability to apply equity than AI reviewers. And AI reviewers are predicted to have 18% more odds of working efficiently than government agent reviewers. However, the difference in efficiency becomes no longer statistically significant after applying the Bonferroni correction. Other than that, human abilities to apply rules consistently to different people are perceived to be the same as AI, a result opposite to what we hypothesize. Novice agents who receive less than 1 year of training are anticipated to be less capable than those agents who have more years of training in all three aspects.

Table 2: Logistic Regression Results

Attributes	Algorithm vs. Government Agent			Within Government Agents		
	Efficiency	Consistency	Equity	Efficiency	Consistency	Equity
Reviewer (Baseline = Algorithm)						
Government agent	−0.200* (0.097)	0.029 (0.090)	0.322*** (0.087)	NA	NA	NA
Reviewer Race (Baseline = African American)						
Caucasian	NA	NA	NA	−0.010 (0.086)	−0.058 (0.084)	−0.174 (0.084)
Hispanic	NA	NA	NA	−0.068 (0.084)	−0.203** (0.082)	−0.074 (0.085)
Reviewer Gender (Baseline = Female)						
Male	NA	NA	NA	−0.091 (0.069)	−0.012 (0.067)	−0.084 (0.069)
Year of Training (Baseline = Less than 1-year of training)						
1-4 years of training	0.598*** (0.077)	0.410*** (0.075)	0.231*** (0.077)	0.614*** (0.083)	0.446*** (0.081)	0.254*** (0.083)
5-6 years of training	0.726*** (0.079)	0.487*** (0.075)	0.317*** (0.077)	0.745*** (0.084)	0.491*** (0.081)	0.332*** (0.083)
Race (Baseline = Caucasian)						
American Indian or Alaska Native	−0.171 (0.197)	0.225 (0.202)	0.183 (0.204)	−0.155 (0.209)	0.230 (0.213)	0.087 (0.215)
Asian or Pacific Islander	−0.593*** (0.120)	−0.593*** (0.116)	−0.640*** (0.117)	−0.670*** (0.128)	−0.603*** (0.125)	−0.741*** (0.126)
Black or African American	0.309*** (0.088)	0.245** (0.084)	0.158 (0.084)	0.333*** (0.095)	0.268** (0.091)	0.147 (0.092)
Hispanic or Latino	0.461** (0.175)	0.143 (0.157)	0.302 (0.165)	0.393* (0.183)	0.114 (0.166)	0.173 (0.173)
Mixed racial background	−0.395 (0.207)	−0.074 (0.214)	−0.376 (0.205)	−0.589** (0.221)	−0.195 (0.229)	−0.587** (0.221)
Gender (Baseline = Female)						
Male	−0.006 (0.068)	−0.038* (0.066)	0.000 (0.066)	−0.053 (0.073)	−0.089** (0.071)	−0.047 (0.072)
Age (Baseline =18 to 24)						
25 to 34	−0.096 (0.141)	−0.041 (0.134)	−0.095 (0.137)	−0.044 (0.148)	0.045 (0.141)	−0.013 (0.146)

35 to 44	0.045 (0.147)	0.199 (0.140)	0.078 (0.143)	0.083 (0.155)	0.293* (0.148)	0.105 (0.152)
45 to 54	0.002 (0.159)	0.030 (0.151)	0.014 (0.155)	0.022 (0.168)	0.107 (0.160)	0.036 (0.165)
55 and over	−0.011 (0.165)	0.199 (0.160)	0.250 (0.164)	0.158 (0.176)	0.351 (0.171)	0.355 (0.177)
Party (Baseline = Democrat)						
Independent	−0.265** (0.093)	−0.217** (0.090)	−0.368*** (0.090)	−0.286* (0.099)	−0.176 (0.096)	−0.339** (0.098)
Republican	0.000 (0.085)	0.048 (0.081)	−0.017 (0.082)	0.035 (0.091)	0.165 (0.087)	−0.027 (0.090)
Ideology (Greater = More liberal)	−0.041 (0.027)	−0.020 (0.026)	−0.002 (0.027)	−0.044 (0.029)	−0.004 (0.028)	−0.004 (0.029)
Education (Baseline = High school or lower)						
Some college but no degree	0.029 (0.148)	0.348* (0.140)	0.054 (0.145)	−0.023 (0.157)	0.324* (0.149)	0.042 (0.156)
Associate degree	0.493** (0.163)	0.522*** (0.150)	0.354* (0.156)	0.634*** (0.178)	0.668*** (0.164)	0.472** (0.172)
Bachelor's degree or higher	0.190 (0.127)	0.529*** (0.119)	0.271* (0.125)	1.171 (0.135)	0.511*** (0.127)	0.284 (0.134)
Incomes (Baseline = Less than $24,999)						
$25,000 to 49,999	0.048 (0.116)	0.010 (0.112)	−0.196 (0.116)	0.066 (0.123)	−0.024 (0.120)	−0.219** (0.126)
$50,000 to 74,999	−0.097 (0.115)	−0.075 (0.112)	−0.187* (0.116)	−0.065 (0.122)	−0.066 (0.120)	−0.231** (0.127)
$75,000 to 99,999	0.281 (0.129)	−0.065 (0.122)	−0.108 (0.127)	0.259 (0.137)	−0.093 (0.131)	−0.083 (0.139)
$100,000 and greater	0.210 (0.137)	0.143 (0.133)	−0.156 (0.135)	0.239 (0.145)	0.107 (0.142)	−0.135 (0.147)
Social welfare eligibility (Greater = More agree)	0.158*** (0.023)	0.193*** (0.023)	0.202*** (0.023)	0.131*** (0.025)	0.174*** (0.025)	0.187*** (0.025)
Social equity priority (Greater = More agree)	0.182 (0.022)	0.143 (0.021)	0.141 (0.021)	0.179 (0.023)	0.147 (0.022)	0.143 (0.023)
Intercept	−0.869*** (0.259)	−0.443*** (0.249)	−1.134*** (0.253)	−0.871*** (0.268)	−1.391*** (0.260)	−0.630* (0.267)
N(observations)	5,820	5,820	5,820	5,023	5,023	5,023

Note: The value without parentheses is the coefficient estimate of the given level. Standard errors are in parentheses. Significance levels are corrected by the Bonferroni correction and established at 0.033. $*p < 0.033; **p < 0.017; ***p < 0.003$.

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 believe that, in comparison to an African American agent, a Hispanic agent may be 18.4% less likely to consistently apply rules to a significant level whereas a Caucasian agent would be less likely to apply equity in their daily work, which becomes not significant after the Bonferroni correction. Similarly, people have reservations about novice bureaucrats for their capabilities to achieve efficiency, consistency, and equity.

We also explore the impacts of participants' racial and gender characteristics on their projection of reviewers' performance as these characteristics are closely related to participants' understanding of representation. When compared to Caucasian participants' viewpoints, Asians or Pacific Islanders are less likely to have positive faith in reviewers' work efficiency, consistency, and ability to apply equity while Black or African Americans are more likely to have higher perceptions regarding efficiency and consistency. In comparison with female participants, males are less likely to believe that decision-makers in the government, either the automated or human ones, would apply rules to different people fairly and impartially. This gender difference is statistically significant before the Bonferroni correction and becomes not significant afterward.

5 Discussion and Conclusion

In this study, we conducted a conjoint experiment to compare human bureaucrats with AI decision-makers in terms of citizens' preferences and perceptions. One of the primary contributions of this study is the examination of citizens' preferences for bureaucrats versus AI in the context of making trivial decisions, i.e., quality control, in which representation is not a salient issue. We find evidence for people's ability to perceive differences between bureaucratic discretion and AI. Furthermore, we disentangle individuals' preferences for the intricate attributes of human and algorithm decision-makers to some degree. We find that citizens tend to choose bureaucrats over AI to make government decisions. However, this needs to be explored further in different contexts with low/high trust government agencies and in different policy areas, such as education, health, and policing. That said, in our study, citizens generally prefer a human agent who is an African American female with substantial training.

When connecting people's preference choices with their ratings, we find that they rate algorithm reviewers to have a higher level of work efficiency but a lower level of ability to apply equity than bureaucrats. These findings suggest the reasons behind people's preferences. It indicates that when employing AI in the government decision-making process, incorporating equity and fairness into the decision-making process in all phases and communicating with people how AI can be trustworthy would be important to improve citizens' acceptance of AI in government (Toreini et al., 2020; Zou & Schiebinger, 2018). This can work in several ways related to TAI. First, when designing the AI system, the development team may want to recruit diverse and multidisciplinary members, with experts focusing on discrimination and bias in the profession. In this way, the system's underlying architecture is likely to incorporate the TAI principle of fairness and promote the interests of both minorities and non-minorities (Toreini et al., 2020). Second, since most AI models must go through a pre-testing phase, this phase can include equity testing. System-level bureaucrats and outsourcing companies responsible for designing the AI system can establish equity metrics and goals that help ensure all groups are sufficiently represented and accurately accounted for in the data-generating processes (Zuiderwijk et al., 2021). To have meaningful tests, public organizations are recommended to adopt feedback lopes and partnerships with a variety of stakeholders, particularly the community of color. Third, public organizations should publish reports regularly to disclose the AI system's decision patterns. By increasing the AI system's transparency and ability to be perceived, we can supervise and minimize discrimination and bias in the data processing and decision-making phase (Glikson & Woolley, 2020).

Looking into human decision-makers' racial and gender identities specifically, we hypothesized that individuals would have more positive attitudes toward in-group bureaucrats. We find partial evidence for this relationship. Indeed, Black participants and female participants are more likely to prefer Black bureaucrats and female bureaucrats, 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 the minority participants in our experimental setting, we do learn that, under the circumstance of unavailable representation, African Americans no longer have a strong preference between out-group bureaucrats and AI decision-makers. These results imply that racially minoritized citizens value government representation and they give preference to those bureaucrats who share their demographic origins. They may view those bureaucrats as more cognizant of their needs and more willing to use their discretion in meeting citizens' needs. This pattern is consistent with past studies of passive and symbolic representation studies that articulate this relationship between racially minoritized citizens and government agents (Miller & Keiser, 2021; Riccucci et al., 2016; Roch et al., 2018).

Together these results provide important theoretical implications for the study of representation and raise several new questions about the interaction between representation, automation, and equity. First, when studying frontline worker decision-making, we frequently focus on the role of representation in high-impact decision scenarios without understanding the underlying mechanism of how representation is salient. If we do not consider the context, we can miss the extent to which representation is salient and under what circumstances it matters more to government service delivery and policy implementation. To this end, our study finds that citizens care about passive representation even in a low-impact decision scenario in social welfare, in which bureaucrats and AI decision-makers are only performing technical and trivial duties. Relatedly, we begin to unpack under what situations AI can be viewed as optimal, e.g., when passive representation is not available. This leaves important questions to discern how or if citizens would still view representation as the most important aspect despite perceived efficiency not being a top priority in their eyes.

Further, 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 choose experienced human decision-makers or AI reviewers over their novice counterparts in welfare applications. However, we caution that this result is context-dependent and needs to be explored in other social services and citizen-state interactions. Other factors about the reviewer may also impact these outcomes, such as previous decisions they have made regarding citizens' applications or if they have worked with other government agencies before. Citizens' appreciation of training has important practical implications for both human resource management and the adoption of AI. For the former, it means that citizens are likely to support maintaining continuous training of current employees and strengthening new employees' training. It also suggests that, 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. Alternatively, if bureaucrats prefer individuals who look like them this implies that agencies need to make a concerted effort to recruit and retain racially minoritized individuals within organizations. Organizations typically focus on retention, but also need to devise a clear strategy to retain individuals of color to create a more inclusive and diverse environment in the positions individuals of color occupy in the organization.

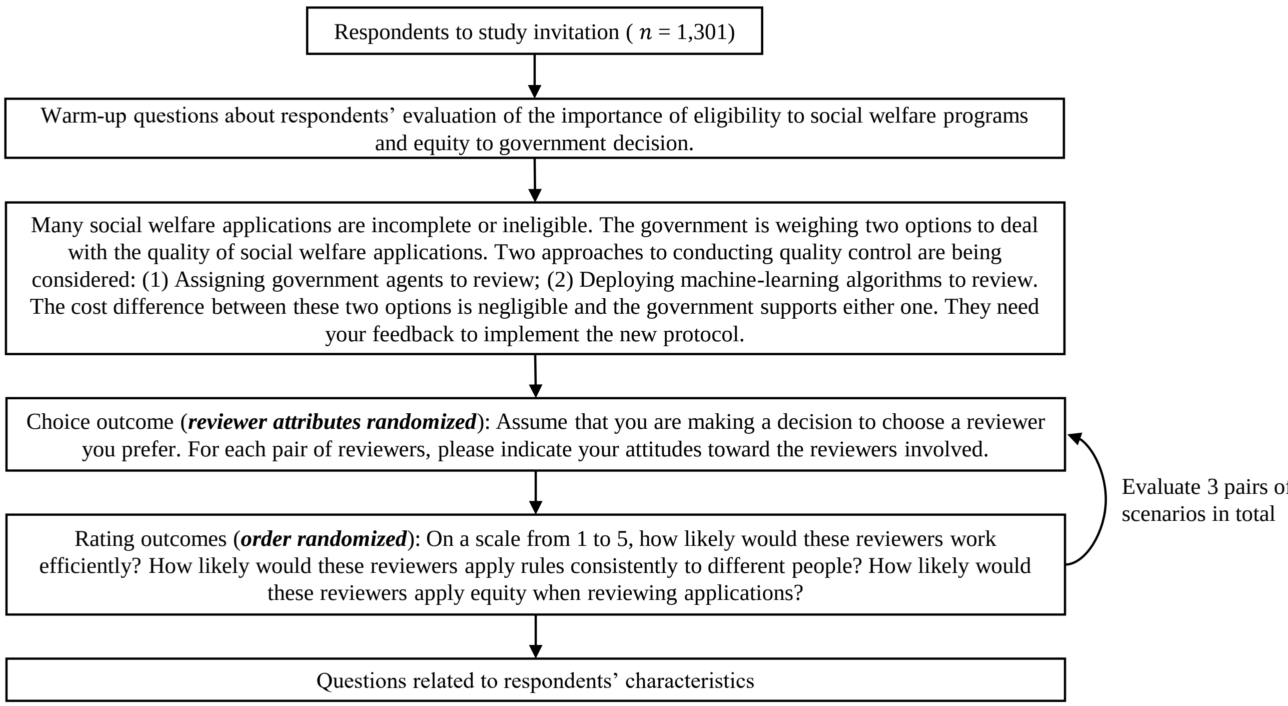
For the employment of algorithms in government decision-making, using the most advanced technology does not always result in improved citizen evaluation. A more tuned AI system may seem to be a safer choice in the citizens' eyes, as the literature on trustworthy AI has suggested that reliability over time is crucial to increasing technology trustworthiness (Glikson & Woolley, 2020). Relatedly, long-term interactions between citizens and AI also reduce people's need for human contact and AI's uncertainty as AI systems becomes more tangible, predictable, and reliable, developing citizens' trust in the algorithm decision-maker (Krämer et al., 2018). As AI systems become more fine-tuned it may cause ripple effects with human employment, or fundamentally shift the role of humans. If individuals can create an AI system that is not only efficient but equitable in its decision-making front-line workers will need to have increased data skills and less interpersonal skills. To account for the increased usage of AI to manage services, schools and human resource training within organizations need to change how they train future employees. Finally, it is worth noting that without further study of the tradeoff between AI and humans making decisions, it is difficult to tell if these results are consistent across policy types, but they can be explored. Additional research can examine what decisions are easily realized by AI and what decisions are more difficult because of the discretionary nature of the interaction between the bureaucrat and the citizen.

Finally, there are several limitations worth noting in our study. First, our experiment does not oversample different groups of minoritized individuals, so some groups 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 minority 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 a human or AI reviewers, and various other factors. Third, our study does not measure participants' understanding of machine-learning algorithms. While this understanding does not necessarily affect our findings because of randomization, including it in the model could have produced more nuances regarding people's preferences between AI and bureaucrats. We recommend future research to measure this and investigate its influence on individuals' preferences.

Despite these limitations, our study provides important insights into how citizens view AI and bureaucrats when reviewing their applications for services. 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 of 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, the investigation into people's preferences of decision-makers in government service delivery inspires discussions about what tasks are appropriate for AI and what for bureaucrats in future government operations. To boost people's trust in government service delivery and decision-making, public organizations and managers should develop and implement assimilation strategies that synergize AI with bureaucratic discretion (Alshahrani et al., 2022). To be specific, the responsibility of making decisions and interacting with citizens for different things should be taken up by different decision-makers. For those services that citizens prioritize equity and fairness, bureaucrats may be more suitable for delivering the services and gaining people's trust. On the contrary, it would be appropriate for AI agents to perform time-sensitive functions that people value efficiency. From this point of view, this study points to a potential direction for future research on AI in government. Researchers and practitioners should pay attention to the technological aspects of AI technologies and the organizational aspects of AI applications in the public sector. By giving nuances to various decisions and services, governments can maximize the benefits of AI and representative bureaucracy and balance the values of efficiency and equity.

Appendix

A Experimental Setup



B Descriptive Statistics ($n = 970$)

Characteristic	Frequency	Percentage	Characteristic	Frequency	Percentage
Gender			Party		
Female	384	39.59	Democrat	407	40.14
Male	586	60.41	Independent	167	16.47
			Republican	419	41.32
Race					
American Indian or Alaska Native	27	2.78	Ideology		
Asian or Pacific Islander	66	6.80	Strongly conservative	177	18.25
Black or African American	225	23.20	Moderately conservative	186	19.18
Caucasian	591	60.93	Neutral	187	19.28
Hispanic or Latino	41	4.23	Moderately liberal	213	21.96
Mixed racial background	20	2.06	Strongly liberal	207	21.34
Age					
18 to 24	58	5.98	Education		
25 to 34	395	40.72	High school or lower	71	7.32
35 to 44	272	28.04	Some college but no degree	107	11.03
45 to 54	140	14.43	Associate degree	93	9.59
55 and over	105	10.82	Bachelor's degree or higher	699	72.06
Incomes					
Less than $25,000	106	10.93	$75,000 to 99,999	163	16.80
$25,000 to 49,999	251	25.88	$100,000 and greater	125	12.89
$50,000 to 74,999	325	33.51			

C Pooled AMCE Results

Attribute	Result
Reviewer (Baseline: Algorithm)	
Government agent	0.103***
	(0.026)
Reviewer Race (Baseline: African American)	
Caucasian	−0.035
	(0.019)
Hispanic	−0.057**
	(0.018)
Reviewer Gender (Baseline: Female)	
Male	−0.037**
	(0.016)
Year of Training (Baseline: Less than 1-year of training)	
1-4 years of training	0.159***
	(0.016)
5-6 years of training	0.298***
	(0.017)
N(observations)	5,820
N(individuals)	970

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

D Heterogeneous Treatment Effects

	Race of Respondent			Gender of Respondent	
Attribute	African American	Caucasian	Other Race	Male	Female
Reviewer (Baseline: Algorithm)					
Government agent	0.166**	0.116***	−0.053	0.087**	0.127**
	(0.053)	(0.034)	(0.066)	(0.033)	(0.044)
Reviewer Race (Baseline: African American)					
Caucasian	−0.109**	−0.016	0.012	−0.046	−0.021
	(0.041)	(0.024)	(0.046)	(0.025)	(0.030)
Hispanic	−0.150***	−0.038	0.001	−0.056*	−0.058
	(0.040)	(0.023)	(0.043)	(0.023)	(0.030)
Reviewer Gender (Baseline: Female)					
Male	−0.013	−0.054**	0.003	−0.010	−0.076***
	(0.034)	(0.020)	(0.038)	(0.020)	(0.024)
Year of Training (Baseline: Less than 1-year of training)					
1-4 years of training	0.123***	0.163***	0.185***	0.146***	0.179***
	(0.033)	(0.020)	(0.038)	(0.019)	(0.026)
5-6 years of training	0.116**	0.345***	0.373***	0.278***	0.328***
	(0.035)	(0.022)	(0.040)	(0.021)	(0.028)
N(total observations)	1,350	3,546	924	3,516	2,304
N(total individuals)	225	591	154	586	384

Note: Participants who reported their racial and ethnicity identities as American Indian, Asian, Hispanic, or mixed racial background are classified into the "Other Race" 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*	0.105	0.160	0.118
	(0.143)	(0.106)	(0.098)	(0.113)
Reviewer Race (Baseline: African American)				
Caucasian	NA	NA	0.064	−0.042
			(0.094)	(0.110)
Hispanic	NA	NA	−0.114	−0.026
			(0.103)	(0.109)
Reviewer Gender (Baseline: Female)				
Male	−0.143	−0.029	NA	NA
	(0.138)	(0.098)		
Year of Training (Baseline: Less than 1-year of training)				
1-4 years of training	−0.016	0.246**	0.098	0.063
	(0.113)	(0.086)	(0.074)	(0.071)
5-6 years of training	0.118	0.179	0.186*	0.125
	(0.126)	(0.084)	(0.073)	(0.073)
N(observations)	124	206	294	274
N(individuals)	56	84	128	126

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

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