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The impact of using algorithms for managerial decisions on public employees' procedural justice

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A R T I C L E I N F O

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A B S T R A C T

Algorithms are used in public management decisions, for instance, to allocate police staff to potential crime scenes. We study how the usage of algorithms for managerial decisions affects procedural justice as reported by public employees. We argue that some public management practices may be more suitable for algorithmic decision-making than others. We hypothesize that employees' perceptions differ depending on the complexity of the practice at hand. We test this through two survey experiments on 109 Dutch public employees and 126 public employees from the UK. Our results show that when a decision is made by an algorithm for practices that are low in complexity, procedural justice increases. Our results also show that, for practices that are high in complexity, decisions involving a public manager are perceived as higher in procedural justice compared to decisions that were made automatically by computers using algorithms. Nevertheless, adding an algorithm to a public manager's decision-making process can increase procedural justice for high complexity practices. We conclude that managers should explore automation opportunities for low complexity practices, but to be cautious when using algorithms to replace public managers' decisions for high complexity practices. In the latter case, transparency about algorithms and open dialogues on perceptions could be beneficial, but this should not be seen as a panacea.

1. Introduction

The idea that data can be used to improve decision-making processes in organizations has become more popular (Anastasopoulos and Whitford 2019; Desouza & Jacob, 2017). At the same time, technological developments have allowed more and novel applications of algorithms to be involved in human decision-making processes (Veale & Brass, 2019; Burton, Stein, & Jensen, 2019). On top of that, algorithms have recently been moved up higher in the hierarchy and are becoming decision-making partners or substitutes at the level of leadership (Wesche & Sonderegger, 2019). In other words, algorithms are increasingly being used for managerial decision-making. For instance, some companies, such as Uber, are almost fully substituting managers by algorithms (Wesche & Sonderegger, 2019). Other examples are that personalized nudges based on algorithms have been implemented within organizations to change employees' behavior (The New York Times, 2018), while data mining has been used for the selection and evaluation of employees (Strohmeier & Piazza, 2013).

Novel utilizations of algorithms are also used for managerial decisions in the public sector. Examples include: the calculating of optimal routes for collecting municipal waste (Karadimas, Papatzelou, and Loumos 2007); analyzing which buildings are more likely to catch on fire to guide which fire safety inspections should be prioritized (Engin & Treleaven, 2019); estimating where the chance of criminal behavior is the highest, and subsequently, send police staff to these so called 'hotspots' (van Zoonen, 2016); the evaluation of teachers' performance (Diakopoulos, 2014; O'Neill, 2016); and, guiding physicians behavior through nudges based on algorithms in health care (Nagtegaal, Tummers, Noordegraaf, & Bekkers, 2019).

Algorithmic decision-making is, however, far from uncontested (Veale & Brass, 2019; Zarsky, 2016). The debate on the value of algorithms focusses on multiple aspects, including accuracy, power and bias. People can moreover display algorithm aversion – which is a tendency to prefer human decision makers over algorithmic ones (Burton, Stein, & Jensen, 2019). In this paper, we focus on the effect of including algorithms in managerial decisions on procedural justice perceptions as reported by public employees. Procedural justice refers to the extent that the process of decision-making is perceived as being fair (Colquitt, 2001; Lind & Tyler, 1988). Procedural justice contributes to perceptions of legitimacy (Mazerolle et al., 2013). Algorithmic decision-making has

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been identified as a problem for the legitimacy of decision-making processes (Danaher, 2016) as they are often opaque and might introduce bias (Janssen & Kuk, 2016).

We expect that perceptions of procedural judgment differ depending on the involvement of the public manager and the algorithm, as well as the complexity of the practice at hand. Building on the work of Zouridis et al. (2020), we distinguish three categories of algorithmic public management. Managers can have either full, partial or no discretion. We test the effect of these different forms of algorithmic-manager relationships on public employees' procedural justice. We hypothesize that the perceptions of procedural justice differ according to the extent to which issues are complex (Busch, Henriksen, & Sæbø, 2018; Noordegraaf & Abma, 2003; Veale & Brass, 2019; Zarsky, 2016). We ask the following research question:

How does the inclusion of algorithms in managerial decision-making affect public employees' procedural justice perceptions of public management practices that differ in complexity?

The contribution of our work lies, first, in giving attention to using algorithms for managerial decisions in the public sector. Thus far, most attention has been directed at automating discretion at the frontline (Bovens & Zouridis, 2002; Reddick 2005; Busch & Henriksen, 2018). Using algorithms for managerial decisions is an underexplored concept (Wesche & Sonderegger, 2019), even though key issues in the public sector, such as tension between rule following and discretion, are relevant at the managerial level as well (Maynard-Moody & Musheno, 2000). We also research the 'middle-ground', when algorithms serve as a decision-making partners rather than substitutes (Wesche & Sonderegger, 2019). This arrangement might be more realistic as, for instance, in Europe, Article 22 of the General Data Protection Regulation prohibits decision-making based on solely automatic processing (Finck, 2019). Through the inclusion of hybrid forms of decision-making, we extend the research by Lee (2018) on the effects of solely automating decisions in general management.

Second, we connect algorithmic public management to procedural justice. Algorithms can only be used for managerial decision-making if algorithms are perceived as legitimate (Wesche & Sonderegger, 2019). A lack of procedural justice can result in the rejection of using algorithms for certain management practices (Sunshine & Tyler, 2003). Thus, we believe that procedural justice has the potential to partly predict in which direction algorithmic public management will develop. In addition, procedural justice affects organizational variables relating to public employees' performance and well-being, such as job satisfaction, performance and organizational citizenship (Colquitt et al. 2001). As such, we explore the potential that including algorithms in managerial decisions has to make a positive or negative contribution. This connects to the societal responsibility of science to explore potential problems and opportunities in novel technological applications (Ghislieri, Molino, & Cortese, 2018). More generally, our paper contributes to the literature on algorithm aversion and antecedents of procedural justice within the public sector (Burton, Stein, & Jensen, 2019; Logg, Minson, & Moore, 2019). We moreover contribute to research on public values as an important determinant of technology adoption, rather than just focusing on the technical aspects of technology (Lupo, 2019; Twizeyimana & Andersson, 2019).

Third, we use an experimental approach. Experiments are especially valuable for detecting causal relationships (Gerber and Green 2012; Margetts, 2011), because they can account for unobserved confounders by randomization. Earlier research on perceptions within governmental organizations has used qualitative methods to detect complexity as an important factor in public employees' acceptance of discretion reduction (Busch et al., 2018). Our research contributes to testing this claim. We expand our experimental results by qualitatively assessing which aspects of complexity are most salient for public employees when algorithms are being used for managerial decisions.

The article will start by elaborating on algorithms, procedural justice, different types of algorithm-manager interactions and how perceptions are linked to management practices that differ in complexity. Then, we will present our hypotheses and explain our experimental method. Subsequently, we present our results and, finally, we end with a discussion and conclusion.

2. Theoretical background

2.1. Algorithms

A technical definition of an algorithm is an 'abstract mathematical structure that has been implemented into a system for analysis of tasks in a particular analytic domain' according to Mittelstadt, Allo, Taddeo, Wachter, and Floridi's (2016) adaption of Hill (2016; p.47). This definition consists out of two important elements. First, the algorithm refers to an *abstract mathematical structure*. Therefore, the algorithm does not imply necessarily the use of techniques, such as machine learning. It could be a simple linear model. Second, this structure has been configured into a *system for analysis*, such as a computer program or software.

The meaning of 'algorithms' yet goes beyond this technical definition. What an algorithm is, is constructed by the discourse surrounding algorithms and by the social context in which an algorithm is deployed (Beer, 2017). Burton, Stein, & Jensen, 2019 showed that, prior to contact with an algorithm, a human will have formed expectations about the algorithm. These expectations can be the product of experiences with algorithms, but also of reports from the media or peers. Research has shown that people can view algorithms as fair or unfair, irrespective of knowledge about the algorithm's procedure or accuracy (Lee, 2018). These perceptions are important as algorithms are often opaque, which causes us to lack information about the processes.

2.2. Types of algorithmic public management

Algorithms and humans can interact in different ways (Jones, 2017; Rahwan, 2018). In this paper we use system-, screen- and street-level bureaucracy to describe different algorithm-manager interactions (Bovens & Zouridis, 2002; Zouridis, van Eck, & Bovens, 2020). Bovens and Zouridis (2002) describe the changing role of public employees through the introduction of new technology. Broadly, the algorithm-manager interaction can take on three forms. First, algorithms can take over the role of the manager when algorithms are fully automated. In other words, technology is decisive. This leaves the manager with no discretion at all. There is little or no human judgment. This is called system-level bureaucracy. An example could be detecting potential problems in civil infrastructure (Spencer, Hoskere, & Narazaki, 2019). The second scenario is when technology informs decisions, but a human decision maker is still required and able to exert judgment. We refer to this as screen-level bureaucracy. An example is predictive policing (Meijer & Wessels, 2019). The third scenario is the classic one in which technology is not necessarily used, but could serve as a support by choice. This is traditional street-level bureaucracy.

2.3. Procedural justice

More attention has been generated for the connection between justice and new technologies, for instance, in the smart city literature on e-justice (Lupo, 2019). Smart cities studies on e-justice have however been criticized for mostly focusing on economic outcomes such as efficiency, while disregarding aspects relating to public value. Nevertheless, in the public sector, public values are essential for the successful adoption of technology (Twizeyimana & Andersson, 2019). In this research, we focus on one of those public values - procedural justice (Page, Stone, Bryson, & Crosby, 2015). Procedural justice recently has been connected to the task-technology fit in studies relating to digitalization in the public sector (Chen, Vogel, & Wang, 2016).

Procedural justice is part of a broader multi-dimensional justice construct consisting of distributive, procedural, informational, and interpersonal justice (Binns et al., 2018; Colquitt, 2001). These dimensions relate to different aspects of justice. Distributive justice, for example, covers one's assessment of the outcome of the decision. Procedural justice is specifically about the extent to which the process underlying decision-making is perceived as being fair (Colquitt, 2001; Lind & Tyler, 1988). Therefore, procedural justice does not necessarily correspond with one's assessment of the outcome. An outcome can be viewed as unfair, while the process with which the outcome was obtained is viewed as fair. Different aspects of justice can correlate (Binns et al., 2018).

Studying procedural justice is important for two main reasons. First, procedural justice has been connected to the use of algorithms because introducing algorithms might undermine the legitimacy of processes (Bovens & Zouridis, 2002; Citron & Pasquale, 2014; Crawford & Schultz, 2014; Danaher, 2016; Parkin, 2011). This can have different reasons as procedural justice is essentially an umbrella term that relates to perceptions on accuracy, consistency, bias suppression, correctability, representativeness and ethics (Greenberg and Colquitt 2005). Therefore, a number of elements can contribute to procedural justice (Rubin, 2007), for instance, the extent to which an employee can voice opinions and can participate in decision-making. On top of that, the rules of the decision-making process, the process used to select those who make decisions and the existence of safeguards are also important (Leventhal, 1980). Second, it has been argued that procedural justice is essential for employees' positive job attitudes and behaviors in public sector organizations. Procedural justice can moreover have important effects on key organizational variables, including outcome satisfaction, job satisfaction, organizational commitment, trust, organizational citizenship behavior, withdrawal and performance (Colquitt et al. 2001).

2.4. Complexity in public management

Theoretical models, such as the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT) model and the Unified Model of Electronic Government Adoption (UMEGA), identify numerous factors that are important for technology adoption (Dwivedi et al., 2017; Venkatesh, Morris, Davis, & Davis, 2003). These models focus on perceptions of technology's characteristics and the environment in which technology has to be implemented, rather than the characteristics of the practice at hand. The task-technology fit model extends these technology adoption models by emphasizing the perceived fit between characteristics of the task and characteristics of the technology (Goodhue & Thompson, 1995).

There is a pervading sentiment in public administration that technology does not fit the nature of public administration, because decisions require human judgment (Oswald, 2018; Veale & Brass, 2019). To use algorithms for decision-making, we must be able to structurally measure, conduct and translate it into a model (Zarsky, 2016). Lipsky (2010) states that "the nature of service provision calls for human judgment that cannot be programmed and for which machines cannot substitute" (p.161). At the same time, rules have been at the center of public administration ever since Weber introduced his ideas on bureaucracy (Weber, 2015). As such, public administration is traditionally characterized by a tension between control and discretion (Busch et al., 2018; Evans & Hupe, 2019; Maynard-Moody & Musheno, 2000).

The call for human judgment in the public sector seems to be associated with the complexity of practices (Busch & Henriksen, 2018; Noordegraaf & Abma, 2003). There is no universally accepted definition of complexity (Mitchell, 2009). In this paper, we present two simplified dimensions of complexity: a technical and normative dimension. Complexity in a technical way boils down to practices consisting of many interconnected parts (Holland, 2014), which might be difficult to measure (Noordegraaf & Abma, 2003). Therefore, complexity can make a reductionist model of reality, in which more data might solve comprehensibility problems, difficult (Mitchell, 2009). Kallinikos (2005) proposed that the goal of contemporary technology is to make practices more manageable and predictable. Therefore, their success is connected to their ability to capture the processes for which they are designed (Kallinikos, 2009). However, complexity generally makes it more difficult to understand practices and predict outcomes. This relates ideas about how public services should be provided. Lipsky (2010), for example, explained that, for street-level bureaucrats, human judgment is necessary as most cases are unique. This uniqueness eliminates IF-THEN types of reasoning and requires discretion from bureaucrats.

Kallinikos (2009) extended his argument by stating that technology integration also depends on the context in which it needs to be embedded. This links to our second dimension of complexity. Complexity in public sector practices has a normative component (Noordegraaf & Abma, 2003). Practices can be contested. Comparable information will mean different things to different people. Trade-offs between values need to be taken into account and discretion should be used to deal with these trade-offs (Janssen & Kuk, 2016; Lipsky, 2010). This makes it impossible to objectively evaluate the 'right' course of action. As such, management cannot be optimal because what appears optimal differs from person to person. This makes practices multi-interpretable or equivocal.

We expect public employees to be in favor of more human judgment for managerial decisions as complexity increases (Busch et al., 2018). This relates to research of Lee (2018), who showed that for 'quantitative' tasks, such as work scheduling based on a predicted amount of customers, algorithms and humans were perceived as equally fair. We however expect that for low complexity tasks, which are conceptualized as quantitative tasks involving a limited number of variables and being relatively uncontested, public employees will be in favor of algorithmic management. In these cases, algorithms can increase accuracy and, using the most accurate option, is uncontested (Grove & Meehl, 1996). This leads to the following hypothesis:

Hypothesis 1. *Decisions involving less human judgment are perceived higher in procedural justice for practices that are low in complexity.*

For tasks involving emotions and human interaction, Lee (2018) showed humans were preferred over algorithms. In line with Lee, we expect that for highly complex practices, humans are preferred. This leads to hypothesis 2:

Hypothesis 2. *Decisions involving less human judgment are perceived lower in procedural justice for practices that are high in complexity.*

3. Methods

We conducted two studies for this article. Our design builds on Lee's (2018) work, but extends it and specifies it to a public management context. Our groups represented three types of algorithmic-manager interactions based on Zouridis et al.'s (2019) typology of system-, screen- and street-level bureaucracy. We based our public management scenarios on real-life algorithmic management. Study 1 was pre-registered under. https://osf.io/xmzr8/:. In this between-subjects study, we researched perceptions of procedural justice in two different scenarios that varied in complexity. Study 2 was developed as a replication of the first study, but used a within-subject design. This allowed us to assess what effect multiple types of decision-making juxtaposed would have (Binns et al., 2018). This study also used different scenarios to test generalizability across various practices. All the conditions are shown in Appendix A. The experimental flow of the Study 1 can be found in Appendix B (Figure B).

3.1. Study 1

In study 1 we studied two public management practices that are low and high in complexity. The practice low in complexity concerned determining how much reimbursement for commuting employees receive. In the Netherlands, rules concerning reimbursement for commuting public employees are settled in collective work agreements. Large organizations have additional rules for issues not covered in those agreements. As such, this practice follows a clear IF-THEN structure and relatively uncontested. This practice is thus low in complexity. Nevertheless, algorithmic advances are being made on travel cost reimbursement, for instance, by employing carpool matching algorithms (Xia et al. 2015).

We used performance evaluation of an employee for our high complexity scenario. Performance evaluation is a highly complex practice as it contains many variables of interest and the relevance of these variables for performance is contested (Van Dooren et al., 2015). Nevertheless, performance can be assessed by using algorithms, for example, in cases of teachers (Diakopoulos, 2014; O'Neill, 2016). We specified that these scenarios concerned back office employees of a municipality. They deal with requests on a case-to-case basis, which we see as central to public administration (Lipsky, 2010). We conducted a pilot study on Prolific. Our sample consisted out of 16 Dutch people, who did not necessarily work in the public sector. The procedure was not different than Study 1, with the exclusion of questions about demographics. We used a mixed ANOVA to estimate our power and expected a medium to large effect. We used the software program G*Power to conduct a power analysis. This provided a needed total sample size of 105.

3.2. Study 2

Study 2, the replication, used two different scenarios varying in complexity to establish generalizability. To reduce possible differences in interpretations of complexity, more information was provided about the factors contributing to the complexity of the practices. The low complexity scenario addressed the calculation of pensions in local government. These calculations are established through collective work agreements in the UK based on a limited amount of variables, such as inflation and pay (Kent Pension Fund, 2020). We considered this scenario as low in complexity as it has a limited number of variables and it is relatively uncontested. Simple calculation tools are available online.

The high complexity scenario involved the hiring of public employees. Selecting employees is a highly normative process that consists out of many intertwined factors (Villegas, Lloyd, Tritt, & Vengrouskie, 2019) and multiple phases (Uggerslev, Fassina, & Kraichy, 2012). Algorithms can be used in different phases of the hiring process, including CV screening and interviewing candidates through natural language processing and is contested (Binns et al., 2018; Raub, 2018).

In this study, we chose customer service officers as the type of employee. Our description of the job as a customer service officer was based on a real job ad. We used the PANGEA app for the calculation of our power based on a Cohen's *d* of 0,4 (Westfall, Kenny, and Judd 2014). This led us to an estimation of 115 participants with 0.99 power. Scenarios were randomized to avoid learning/fatigue effects.

Other factors were kept constant. The process was opaque for both studies, practices possibly could have large consequences for employees, and outcomes were not specified. The conditions are shown in Appendix A.

3.3. Measures

Our dependent variable is procedural justice and consisted of a direct measure. Greenberg and Colquitt (2005) recommend using a direct measure when procedural justice is a dependent variable, and when event characteristics serve as the independent variable. We opted for a measure based on Lind and Tyler (1988) asking, for example, 'How fair is the procedure by which the performance of back office employees is evaluated? '. Respondents could then select a number from 1 ("Extremely unfair") to 7 ("Extremely fair") on a 7-point Likert scale. We then asked participants to explain their reasons for their ratings in an open-ended question. This allowed us to analyze to what extent complexity and elements of procedural justice played a role in the ratings for procedural justice. Our survey also measured subjects' managerial status (i.e., whether participants were in charge of managing subordinates), age, gender, educational background, and field of employment.

3.4. Procedure

3.4.1. Study 1

Data was collected through an online survey using the alumni panel of the Utrecht School of Governance, which consisted mainly of public employees (75%). Participants were thus all higher educated and located across the Netherlands. We collected data for 109 Dutch public employees and excluded employees in the private sector from our analysis. Participation was voluntary. The survey was distributed through e-mail in the beginning of July 2019. Randomization was done in the Qualtrics survey software. We randomized participants to one of the three conditions. In this way, respondents received the two scenarios with the same algorithm-manager interaction. We made the decision-maker bold to emphasize how the decision was made. The manipulation check question asked was: "Which of the following made the decisions in the situations that you read?"

3.4.2. Study 2

Data was collected through an online survey using Qualtrics survey software and crowdsourcing platform Prolific Academic. Participants were pre-screened on residing in the UK and being an employee of a local, regional or national governmental organization. Each participant was presented with all scenarios and all possible decision-makers. We collected data on 126 public employees. The survey was distributed in the beginning of April 2020.

3.5. Analyses

For both studies, *p*-values are reported based on two-tailed hypotheses. We qualitatively analyzed participants' reasons for their answers to questions about procedural justice (Strauss & Corbin, 1998). We did this, first, by openly coding all quotes in our dataset. Afterwards, we axially coded our concepts by combining our codes into meaningful groups. The last step was to connect common codes to the concepts in our experimental design, leaving room for induction. The original data of Study 1 and Study 2 is available online (Appendix D). The answers were translated into English and sentences were sometimes adapted to make them grammatically correct. Demographic data were removed from Study 1 to guarantee anonymity.

For Study 1, we conducted a mixed ANOVA. In case of an interaction effect, further ANOVAs on the separate conditions are conducted. Which conditions significantly differed, was analyzed by adopting the Games-Howell post-hoc test.

For Study 2, we conducted a two-way repeated measures ANOVA. When there was an interaction effect, we further proceeded to determine simple main effects per scenario by using repeated measure ANOVA's. Differences between conditions were tested using post-hoc *t*-test using the Bonferroni correction.

4. Results

4.1. Quantitative analyses

For study 1, the randomization check shows that our descriptive conditions are distributed equally among groups. All descriptives per group are shown in Appendix C (Table C.1). The manipulation check indicates that the manipulation was successful (X^2 (4, N = 100) = 127.38 p = 0.00). Exclusion of those who failed the manipulation check leads to similar results. Our mixed ANOVA presents a significant interaction effect of complexity and the different types of decision-making (F (2, 106) = 44.09, $p < 0.001$). Thus, the effect of how decisions are made on procedural justice is different in the two scenarios varying in complexity. We conducted two separate ANOVAs on both complexity conditions to interpret this effect. A significant omnibus result was found (F(2, 107) = 35.21, p < 0.001) for the scenario low in complexity on travel cost reimbursement. Post hoc comparisons using the Games-Howell test indicated significant differences between the algorithmic (N = 40, M = 5.70, SD = 1.04) and public manager condition (N = 37, M = 3.05, SD = 1.65) (p < 0.001, Cohen's d = 1.96), as well as for the algorithmic and combination condition (N = 33, M = 3.70, SD = 1.61) (p < 0.001, Cohen's d = 1.53). Differences between the combination and manager condition were not significant (p = 0.23, Cohen's d = 0.40). This indicates a medium effect size.

The ANOVA was significant for the scenario high in complexity as well (F(2, 106) = 9.23, $p < 0.001$). A post hoc Games-Howell test again indicated the algorithmic (N = 40, M = 3.13, SD = 1.34) and manager condition (N = 36, M = 4.31, SD = 1.43) to differ (p < 0.001, Cohen's d = 0.86), as well as the algorithmic and combination (N = 33, M = 4.33, SD = 1.43) condition (p < 0.001, Cohen's d = 0.88). The difference between the combination condition and the manager condition was not significant (p = 1.00, Cohen's d = 0.01). Results are displayed in Fig. 1.

For Study 2, the within-subjects replication , the two-way repeated measures ANOVA indicated a significant interaction effect of complexity and conditions (F(1.38, 172.45) = 103.68, p < 0.001). Descriptives are shown in Appendix C (Table C.2). Thus, the effect of the type of decision-making was again different in the two scenarios varying in complexity. We conducted a paired t-test to explore the main effect of complexity and two ANOVAs on both complexity conditions to interpret this effect.

For ANOVA on the scenario low in complexity, the calculation of pensions, showed a significant result (F(1.4, 180.9) = 46.55, p < 0.001) of the decision-maker on procedural justice. Post-hoc t-tests with the Bonferroni correction indicated significant differences between the algorithmic (M = 4.84, SD = 2.08) and public manager condition (M = 3.20, SD = 1.90) (p < 0.001, Cohen's d = 0.74), as well as the algorithmic and combination condition (M = 4.03, SD = 2.02) (p < 0.001, Cohen's d = 0.38) and the public manager and combination condition (p < 0.001, Cohen's d = 0.70).

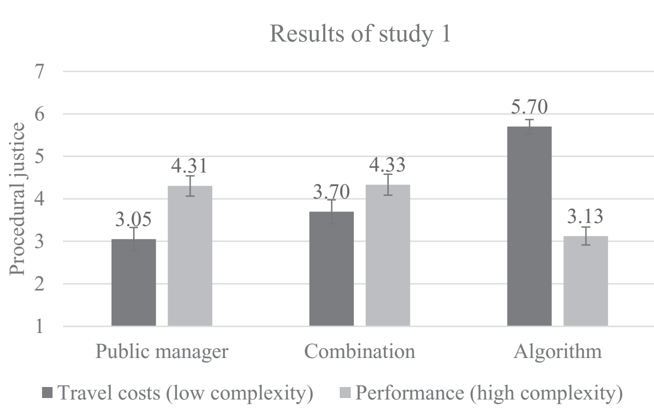

Fig. 1. Means of procedural justice per group with standard error bars for study on a 7-point Likert scale.

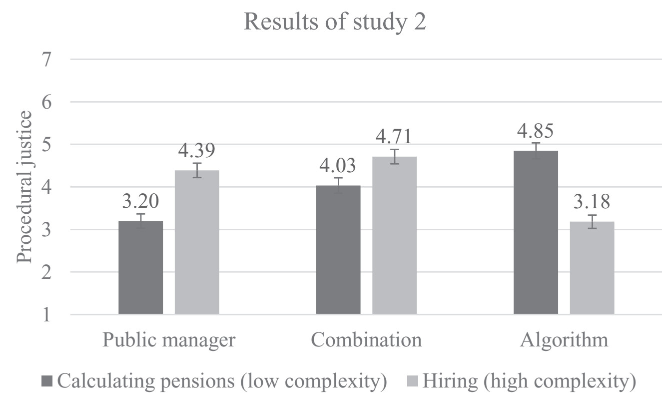

Fig. 2. Means of procedural justice per group with standard error bars for study 2 on a 7-point Likert scale.

For the scenario high in complexity concerning hiring, a significant result (F(1.7, 218.5) = 59.65, p < 0.001) was found as well of the decision-maker on procedural justice. Post-hoc t-tests with the Bonferroni correction indicated significant differences between the algorithmic (M = 3.18, SD = 1.74) and public manager condition (M = 4.39, SD = 1.90) (p < 0.001, Cohen's d = 0,62), as well as the algorithmic and combination condition (M = 4.71, SD = 1.91) (p < 0.001, Cohen's d = 0.98). The combination and manager condition were significantly different as well (p = 0.035, Cohen's d = 0,22). Results are displayed in Fig. 2.

4.2. Qualitative analysis

Our qualitative analyses revealed why these results occurred. We present the most important results below. First, we see that, in low complexity scenarios, algorithms are favored over managers, because managers are seen as subjective and biased, whereas computers using algorithms are seen as objective. To illustrate, respondents in Study 1 emphasized that judgment should be based on rules, such as the collective work agreement, and not on any one individual's judgment. In the algorithm condition, it was mentioned that the decision was based on "*facts*" or "*hard data*" and "*rules*", which are measurable. It was noted that the decision should be based on "*established frameworks*" (R73S1) and that "*It is not up to an individual within an organization to make such a decision*" (R24S1). Respondents in Study 2 mentioned that algorithms were favored over managers because "*managers are biased*" and computers are "*objective*" ensuring an equal process. R99S2 for instance noted "*Having a person making the decision means that he may be influenced by outside factors, whereas a computer would not be.*" And R40S2 noted "*The managers judgement may be unfair and not equal to others whereas a computer is not biased.*"

Nevertheless, some respondents mentioned it was positive that humans 'assisted' the algorithm, for instance, when algorithms err or when there are specific justifying circumstances. This explains why a combination is seen as more just in both studies for the low complexity decisions than decisions by a manager alone. R121S1, for example, said: "*If every employee is judged on the basis of equal criteria, it seems quite fair to me. If the personal situation requires a different treatment than that proposed by the computer, I think that the manager should be able to deviate from this.*" R115S2 mentioned "*Calculating pensions is a mathematically precise function with little room for human judgement. Using an algorithm for it is likely to produce more accurate and consistent results. There should always be room for human intervention to quality assure of check for errors, but the majority of the work should be calculated automatically*." R15S2 mentioned "*Judgement alone may be biased, and an algorithm alone may not take into account any special circumstances.*"

In high complexity conditions managers or manager-algorithm combinations are favored over solely using algorithms. This is mainly because soft aspects (such as compassion and fit within the team) and practices (such as face-to-face interviews in Study 2) are seen as being impossible for an algorithm to consider. R41S1 for instance mentioned "*A large part of the requests that come to them will be specific, and then compassion, solution-oriented approach, service, creativity, etc. are more important properties in proper functioning. That is difficult to measure with an algorithm*." R76S2, for instance, mentioned "*Hiring relies far more on variables, which a computer algorithm is unable to process. Judging personality, values and fit with a team is not possible for algorithms.*" Some respondents mentioned that this required the skills from managers, which some respondents mentioned comes down to a "*feeling*".

Combinations of decision-makers are, in general, highly recommended in Study 1. Respondent R19S1 for instance mentioned: *"If everything functions like it should, the manager has a good view of the performance of its own employees. Then it is logical and good that he uses his own experience and judgment in the assessment. It would be good if that assessment is supplemented with more objective data and / or the opinion of others within the organization."*

Nevertheless, combinations of algorithms and managers are only favored statistically in high complexity decisions when presented juxtaposed. In Study 2 respondents often mentioned that humans and computers have the ability to complement each other. An example is when R19S2 mentioned "*Humans and machines can make a mistake whilst working on their own. Working together ensures greater accuracy*." However, in high complexity cases, the algorithm was more often preferred as assisting the human, instead of the other way around, as seen in the low complexity scenarios. Respondent R103S2 for instance mentioned *"A public manager can make a good judgement call, assisted by algorithm. A computer can't judge on a person's warmth and feeling."*

5. Discussion

Algorithms are increasingly applied in public management decision-making. However, this could be problematic for the legitimacy and acceptance of decisions. This paper sought to answer the question: *How does the inclusion of algorithms in managerial decision-making affect public employees' procedural justice perceptions of public management practices that differ in complexity?*

Our results have two main implications. First, public employees' procedural justice changes most when algorithms are fully automated and are replacing public managers. The direction of the effect, however, depends on the complexity of the practice at hand. For low complexity practices, automated algorithmic decision-making leads to higher reports of procedural justice, while the opposite effect occurs for high complexity practices. The attention for specific characteristics of the algorithm changes with the complexity of the practice. For low complexity practices, public employees indicate that they prefer algorithmic decision-making because it guarantees equal treatment across employees and is based on rules. The algorithms are seen as objective; thus, a controlled Weberian ideal of bureaucracy can be achieved by automating an algorithm (Weber, 2015). Decision-making by a public manager is less trusted, seen as subjective and reminds employees of special treatment. This differs from Lee (2018) who reported that for quantitative tasks, such as checking certain components of machinery, human and algorithmic decision-makers are viewed as equally fair. The quantitative tasks Lee (2018) researched can however be seen as more complex than the low complexity scenarios in this article. This indicates that the relationship between preferring an algorithm to a manager is linear based on complexity. In other words, less complexity of the practice means more preference for algorithms as a decision-makers. Apart from that, the difference between this article and Lee (2018) could be explained by this study's focus on procedural fairness, as opposed to general fairness, or could indicate that different values matter to public employees (Moore, 1995). Future research should replicate this study in the private sector.

For high complexity practices, decisions involving a public manager are perceived as higher in procedural justice than decisions that are made automatically by computers based on algorithms. This difference can be attributed the belief that algorithms cannot deal with practices that involve and attributed to rely on human skills, such as compassion and creativity. Public employees consider these factors as hard to measure. Thus, in highly technical complex practices, algorithms are not seen as being able to substitute for human judgment because of the nature of human interaction and service provision (Lee, 2018; Lipsky, 2010). Apart from that, public managers are trusted to judge performance and managers skills, which involve 'feeling', are welcomed in high complexity practices such as hiring and performance assessment. This corroborates Busch et al.'s (2018) findings that professional discretion is preferred for complex practices. As such, we expect algorithms to become at best decision-making partners, instead of algorithms becoming substitutes for public managers for highly complex practices (Wesche & Sonderegger, 2019).

Second, *adding* an algorithm to managerial decision-making can be beneficial. Benefits, nevertheless, depend on the practice at hand. For low complexity practices, hybrid decision-making is viewed more favorable than managers' judgment alone. For high complexity practices, a combination is only deemed more favorably when juxtaposed with the alternative of only having a public manager decide. The latter does not corroborate our second hypothesis and indicates the relationship between involving algorithms and procedural justice is not simply linear for highly complex practices. Future research should test if these effects also occur in real-world scenarios, for instance, by testing the effect of adding an algorithm to hiring practices on public employees' procedural justice.

Finally, we make two practical recommendations for public managers. The first recommendation is that automating decision-making in highly complex practices is not recommended, whereas automating low complexity practices is. When automating decision-making in high complexity practices is still preferred within organizations, public managers could pay attention to transparency and expectations in order to counter resistance to algorithmic decision-making. Transparency implies providing details on different aspects of an algorithm, such as platform design and algorithmic mechanisms (Ananny & Crawford, 2018). Transparency might be a solution, as transparency can generate trust (Kizilcec, 2016). However, a pitfall is that offering superficial information might give the illusion of transparency and not actually increase understanding of the workings of the algorithm (Janssen & Kuk, 2016). Apart from transparency, an open dialogue could help managers increase understanding of public employees' perceptions of algorithmic decision-making. In this way, public managers can take employees' expectations regarding decision-making into account.

Second, hybrid decision-making should be considered when public managers are operating alone. Moving from exclusively managerial to hybrid decision-making increases procedural justice for low complexity practices and, at least, does not decrease procedural justice for high complexity ones. In the latter case, the benefit of adding an algorithm will depend on different factors, such as trust in the manager and the performance of the algorithm. This might differ from case-to-case. More research on real life cases is needed to identify these factors and their relationships with each other.

6. Limitations

Our first limitations relate to the design. The scenarios varied on practice complexity. However, complexity consists of a technical and a normative dimension. We treated complexity as one construct in this article. As such, our experimental research did not allow us to assess the causal effect of the individual dimensions. Future research should study these dimensions separately. In addition, some respondents indicated that, for them, a managers' judgment implied that the manager did not follow rules. Future research could test perceptions on managerial, hybrid and algorithmic decision-making when the same rules are explictly followed. Lastly, our survey experiments suffered limitations similar to those reported in other online experiments (Manfreda, Batagelj, & Vehovar, 2006).

Our second limitations relate to the scope of our research. This research only tests perceptions on the management of public employees, such as back office workers and customer service officers. Future research needs to test effects in other public sectors, such as health care, education and policing, or for other practices, such as predictive policing. Also, we focused on how algorithmic management was perceived when practices differed in complexity. Other factors can influence perceptions as well. Examples are the number of cases that must be processed and if the organization is part of a centralized system (Bovens & Zouridis, 2002). Apart from that, future research should pay attention to the interplay between daily technology use at work and views on algorithmic decision-making (Scheerder, van Deursen, & van Dijk, 2017).

Author statement

This work is single authored by Rosanna Nagtegaal.

Declarations of interest

None

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Appendix A. Experimental conditions

A.1. Experimental conditions Study 1

We would like to ask you to judge the following scenarios. These scenarios are about managing back office employees in a municipality. Back office employees treat various requests from citizens, varying from providing documents to granting authorization. There is a trade-off between individual and collective interests per case.

Low in complexity practice

In a municipality a [**computer, using an automated algorithm/a public manager, using his own judgment and an algorithm/a public manager using his own judgment**] decides which travel reimbursement for commuting a back-office employee is entitled to.

How fair is the procedure by which it is decided by which travel reimbursement back office employees is entitled to?

High in complexity practice.

In a municipality a [**computer, using an automated algorithm/a public manager, using his own judgment and an algorithm/a public manager using his own judgment**] evaluates the performance of a back-office employee.

How fair is the procedure by which the performance of back office employees is evaluated?

A.2. Experimental conditions Study 2

The practices were presented randomly to participants.

Low in complexity practice.

The first practice is calculating pensions for Customer Service Officers. The calculation is based on a limited number of factors such as pensionable pay and inflation. The calculation is determined by law.

High in complexity practice.

The second practice is hiring Customer Service Officers. Hiring is based on a large amount of factors including fit with local governments values, fit within the team dynamics and employees' skills in service provision. The hiring process moreover consists out of multiple phases including the scanning of CVs and interviewing potential candidates. Opinions about which specific factors matter most differ.

How fair is the procedure for [practice] for the Customer Service Officer when decisions are being made by:

- A public manager, using his own judgment.
- A public manager, using his own judgment and an algorithm.
- A computer, using an automated algorithm.

Appendix B. Experimental flow

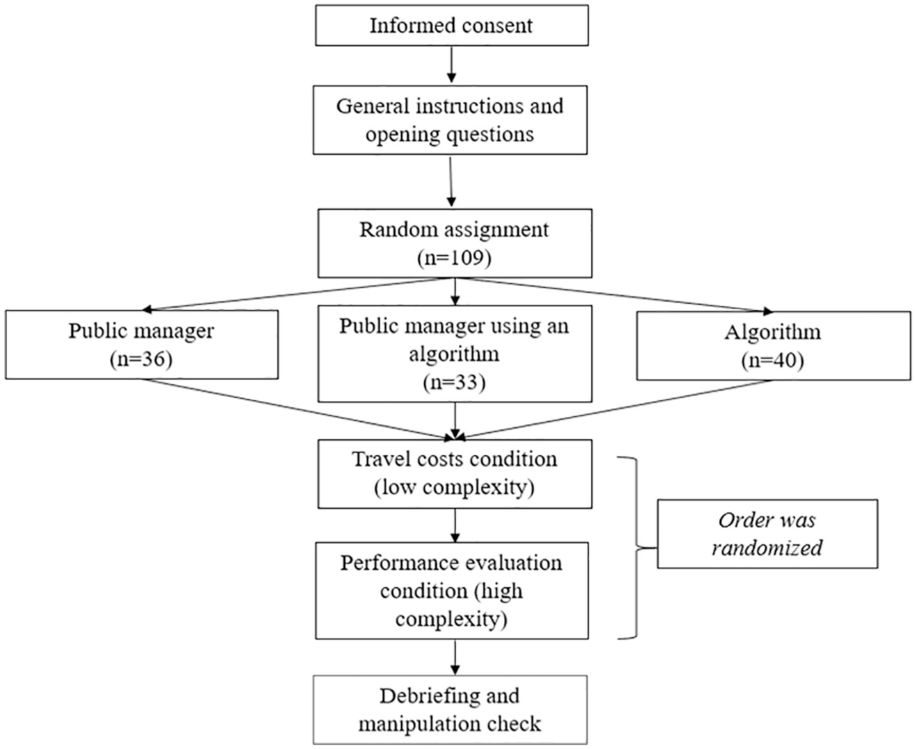

Fig. B. Experimental flow study 1.

Appendix C. Demographic data Study 1 and Study 2.

Table C.1
Descriptives and differences per group per condition for Study 1

Variable	Public manager	Public manager using an algorithm	Algorithm	All
% female	57%	47%	55%	53%
% manager	33%	45%	40%	39%
Average year of birth	1977	1976	1977	1977
Public sector				
Health care	19%	24%	30%	25%
Education	22%	9%	18%	17%
Government	39%	27%	40%	38%
Other	19%	39%	13%	23%

Note. All differences between groups were tested through Chi-square tests, except the difference for age, which was calculated using an ANOVA. $p < 0.05 = *$

Table C.2
Descriptives for Study 2

Variable	All
% female	75%
% manager	43%
Average year of birth	43
Public sector	
Health care	16%
Education	41%
Government	20%
Other	20%

Appendix D. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.giq.2020.101536.

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