Decision-makers’ Processing of AI Algorithmic Advice: ‘Automation Bias’ versus Selective Adherence

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Abstract. Artificial intelligence algorithms are increasingly adopted as decisional aides by public organisations, with the promise of overcoming biases of human decision-makers. At the same time, the use of algorithms may introduce new biases in the human-algorithm interaction. A key concern emerging from psychology studies regards human overreliance on algorithmic advice even in the face of “warning signals” and contradictory information from other sources (automation bias). A second concern regards decision-makers’ inclination to selectively adopt algorithmic advice when it matches their pre-existing beliefs and stereotypes (selective adherence). To date, we lack rigorous empirical evidence about the prevalence of these biases in a public sector context. We assess these via two pre-registered experimental studies (N=1,509), simulating the use of algorithmic advice in decisions pertaining to the employment of school teachers in the Netherlands. In study 1, we test automation bias by exploring participants’ adherence to a prediction of teachers’ performance, which contradicts additional evidence, while comparing between two types of predictions: algorithmic v. human-expert. We do not find evidence for automation bias. In study 2, we replicate these findings, and we also test selective adherence by manipulating the teachers’ ethnic background. We find a propensity for adherence when the advice predicts low performance for a teacher of a negatively stereotyped ethnic minority, with no significant differences between algorithmic and human advice. Overall, our findings of selective, biased adherence belie the promise of neutrality that has propelled algorithm use in the public sector.

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Introduction

Artificial intelligence (AI) algorithms are being widely adopted in the public sector across jurisdictions. Essentially a set of tools that display (or can even surpass) human-level performance on given tasks, traditionally associated with human intelligence, AI algorithms are being relied upon in areas as varied as policing, welfare, criminal justice, healthcare, immigration or education (Citron 2008; Diakopoulos 2014; O’Neil 2016; Ferguson 2017; Eubanks 2018; Yeung 2018; Yeung and Lodge 2019; Shark 2019; Veale and Brass 2019; Busuioc 2020), increasingly permeating non-routine and high-stakes aspects of bureaucratic work. Algorithms are thus being used by schools to inform individual teacher firing decisions (O’Neil 2016) or to predict student grades for university admissions (Broussard 2020), by judges in bailing and sentencing (Angwin et al. 2016), by police for facial recognition or to predict crime and to inform resource allocation decisions in the context of predictive policing technologies (Ferguson 2017; Richardson et al. 2019). The growing (and deepening) reliance on AI and machine learning technologies – i.e. algorithms that learn on their own – in the public sector has not surprisingly been diagnosed as “transformative” of public administrations (Busch and Hendriksen 2018; Young, Bullock and Lecy 2019; Bullock 2019).

These developments are driven by the promise of policy solutions that are more effective, efficient and low-cost. In addition, and importantly, algorithms come with the promise of neutrality, in contrast to decision-making based on human intuition, which involves biases, and can result in discrimination. In other words, AI use in public sector decision-making is said to hold the potential to help us overcome our cognitive biases and limitations. Seemingly ‘objective’ data-driven technologies offer a way to bypass well-documented human biases. This has been an important driver for the adoption of such technologies in highly consequential public sectors areas such as policing or criminal justice: Predictive policing technologies for instance, propagated and gained popularity in the US context “as one answer to racially discriminatory policing, offering a seemingly race-neutral, ‘objective’ justification for police targeting of poor communities” (Ferguson 2017, 5). Numerous other jurisdictions have now followed suit with predictive
technologies relied upon by police forces in UK, the Netherlands, Germany, among many others. Like rationales have hastened the adoption of predictive risk assessment systems in criminal justice, similarly in no small part in response to concerns with human bias and discrimination (Israni 2017). The perceived ‘neutrality’ or ‘objectivity’ of algorithmic decision-making – compared to ‘biased’ human decision-making – has been critical to the case for their adoption in the public sector and beyond (Benjamin 2019).

Due, in no small part, also to a variety of legal constraints, AI algorithms currently serve for the most part as decisional aides to human decision-makers in a public sector context. Rather than making decisions on their own, algorithmic outputs – be they the risk assessment scores used in criminal justice or the algorithm-generated ‘heat maps’ of predictive policing – inform human decision-making. In this context then, algorithmic decision-making refers to “the use of algorithms as an aid (rather than a substitute to human analysis), to inform and improve the quality of human decisions or actions” (Busuioc 2020).

For all its promise, the deployment of AI algorithmic technologies in the public sector has raised important concerns. High among these are concerns with algorithmic accountability and our ability to challenge algorithmic outputs (Diakopoulos 2014; Busuioc 2020); issues of “algorithmic bias” – the well-documented propensity of algorithms to effectively learn systemic bias through their reliance on historical data and come to perpetuate it, effectively “automating inequality” (Eubanks 2018); as well as the potential for bias arising from human processing of AI algorithmic outputs. This paper focuses on the latter, which we believe is an important and especially worthy aspect of analysis due to the fact that currently algorithms for the most part function as decisional aids. While in principle algorithmic decision-making can be both mixed or fully-automated, as noted above AI algorithms for the most part inform rather than altogether supplant human decision-making (see also Edwards and Veale 2017). This is especially so in highly consequential public sector areas, where “full automation seems inappropriate or far off” (Ibid). As such, algorithms do not remove the human decision-maker out of the equation – rather, algorithmic decision-making arises at the interaction
of the two. With AI said to have “have profoundly changed the practice of decision making in organizations” (Young, Bullock and Lecy 2019), it becomes stringent therefore to understand how human decision-makers process algorithmic outputs, how they incorporate such outputs into their decision-making, their implications and whether these differ in significant ways from the processing of traditional (human-sourced) advice.

In this paper, we focus on two diverging biases. The first bias, which builds on previous social psychology studies is “automation bias”. It refers to a well-documented human propensity to automatically defer to automated systems, despite warning signals from other informational sources. In other words, human actors are found to uncritically abdicate their decision-making to automation. While robust, these findings have been documented for AI algorithmic precursors such as pilot navigation systems (albeit some anecdotal evidence is emerging with respect to AI technologies too), and in fields outside a public sector context. The second bias we test, which can be extrapolated from existing public administration research on biased information processing, pertains to decision-makers’ selective adherence to algorithmic advice. Namely, the propensity to adopt algorithmic advice selectively, when it matches pre-existing stereotypes about decision subjects (e.g. when predicting high risk for members of minority groups). While not yet investigated in our field (with respect to algorithmic sources), incipient studies from law and computer science do report some supporting evidence consistent with the latter, albeit with mixed results. These studies also have several key limitations, most importantly: they did not compare algorithmic advice to equivalent advice by human experts. Hence, we do not know if these tendencies are phenomena which are inherent to algorithms, or more emphasized for such advice, compared to advice by human experts. This distinction has important theoretical implications with regards to our understanding of the mechanisms underlying these biases, as well as practical implications regarding the design of strategies and interventions for mitigating such biases.

We report the results of two survey experiments, which provide rigorous tests for these hypothesized biases. The experimental design simulates the use of algorithmic advice in
decisions pertaining to the employment of school teachers. In study 1, we put automation bias to a rigorous test by exploring participants’ adherence to a seemingly inaccurate algorithmic prediction (which contradicts additional evidence) and comparing it to an equivalent human-expert based prediction. In study 2, we replicate these findings, and at the same time, we also test whether the teachers’ ethnic background moderates decision-makers’ inclination to follow the algorithmic advice. In other words, whether decision-makers are more likely to follow algorithmic advice when this advice corresponds to their pre-existing biases (engaging in ‘selective’ rather than automatic adherence).

Our focus is on human processing biases arising from the use of AI algorithms in a public sector context. While we would expect such biases to be equally relevant for algorithmic decision-making in the private sector, we focus on the public sector because the stakes are especially high for governments. AI algorithms are increasingly adopted in high-stakes areas – i.e. where they are highly consequential for individual’s lives, rendering these questions especially pressing in a public sector context. Our theoretical and empirical focus is specifically on AI algorithms as decisional aides, but given thus-far limited theorizing on this topic with respect to AI algorithms, earlier studies on automation and automated decisional aides offer useful starting points for our investigation.

**Automation Bias: Automatic Adherence to Algorithmic Advice**

While AI is meant to help us overcome our biases, research from social psychology suggests that automated systems might give rise to new and distinct biases arising from human processing of automated outputs. “Automation bias” is a well-recognised decisional support problem that has emerged from studies in aviation and healthcare, areas that have traditionally heavily relied on automated tools. Automation bias refers to undue deference to automated systems by human actors that disregard contradictory information from other sources or do not (thoroughly) search for additional information (Parasuraman and Riley 1997; Skitka, Mosier, and Burdick 1999; Skitka, Mosier and
In other words, it is manifest in the “the use of automation as a heuristic replacement for vigilant information seeking and processing” (Mosier et al. 1998, 201), a “short cut that prematurely shuts down situation assessment” (Skitka et al. 2000). Extant studies suggest that this propensity to defer to automation stems on the one hand, from the perceived inherent superiority of automated systems by human actors and on the other, from “cognitive laziness” or a human reluctance to engage in cognitively demanding mental processes, including thorough information search and processing (Skitka, Mosier, and Burdick 2000, 702). Moreover, it has been suggested that algorithms act as a “moral buffer” leading to “psychological distancing” when applied to decisions with tangible consequences on individuals (Cummings 2006).

Experimental lab studies have demonstrated this tendency across a number of research fields (Goddard, Roudsari, and Wyatt 2012, 123). These research findings are further supported by ample anecdotal evidence of automation bias with respect to commercial flights (Skitka et al. 2000, 703), cars navigation systems (Milner 2016) and more recently, also specifically documented in the context of AI, for self-driving cars (National Transportation Safety Board 2017). Recent business management experiment-based studies similarly talk about “algorithm appreciation” (Logg, Minson, and Moore 2019), describing a similar tendency to over-trust algorithmic outputs. Yet, they also propose that people tend to be less tolerant to errors by algorithms compared with similar human errors (Dietvorst, Simmons, and Massey 2015; 2018).

Studies within this body of research broadly differentiate between two types of decision errors which automation bias can take, termed “errors of commission” and “errors of omission” (Skitka, Mosier, and Burdick 1999). The first type pertains to people actively following a false recommendation by an automated decision aid, in spite of counter-evidence from other available sources of information. The second type pertains to people ignoring anomalies and irregularities when these are not indicated by the automated
system. The latter is more specific, and applies to automated warning systems aimed at identifying anomalies or irregularities that may require people’s intervention (such as warning systems in aircrafts and vehicles, or spelling check software). Since in a public context algorithmic decisional aids are normally used as tools for predicting specific outcomes (e.g. recidivism or the risk of not appearing for court) and not as warning systems, our focus is mainly on the first type – commission errors.

While studies on automation bias and AI are for now still lacking (evidence pertains primarily to automated and algorithmic tools that precede AI and are outside a public administration context), concerns with automation bias or undue deference to AI algorithms are recurrently voiced by academic scholars in a context of growing reliance on AI tools in the public sector and high stakes scenarios (e.g. Citron 2008; Cobbe 2019; Zerilli et al. 2019; Medium – Open Letter Concerned AI Researchers 2019). These concerns also echo early calls in our field about the potential of AI for “atrophying administrators own judgement and sense of responsibility” (Barth and Arnold 1999), the risk of “overly passive or deferential human beings” (Ibid). More broadly, it also speak to a broader strand of literature on the implications of AI for the exercise of bureaucratic discretion and professional judgment (Busch and Henriksen 2018; Bullock 2019; Young, Bullock, Lecy 2019) i.e. the potential of digital tools to supplant human discretion and to “influence or replace human judgement in public service provision” (Busch and Hendriksen 2018).

Such concerns become particularly relevant given well-documented failures and malfunctioning of AI(-informed) systems (e.g. Angwin et al. 2016; O’Neill 2016; Buolamwini and Gebru 2018; Snow 2018; Ferguson 2017, 2020; Eubanks 2018; Richardson et al. 2019; Benjamin 2019; Coalition for Critical Technology 2020; Broussard 2020). Due to their reliance on historical data (as training data) AI algorithms have been found to reproduce and automate historical bias, and do so in ways that, by virtue of their opaqueness and/or high complexity, have proven difficult to timely diagnose for both domain experts and system engineers alike (see Busuioc 2020). Algorithmic systems in criminal justice or policing for instance, come to embed and
propagate the biases of their training datasets (i.e. racially discriminatory practices in law enforcement and criminal justice – from arrest rates to sentencing practices), giving rise to inescapable feedback loops. A human propensity for deference to algorithmic systems under such circumstances would become especially problematic – even more so given the high-stakes of AI use in a public sector context.

Hypotheses:

$H_1$ - Policy-makers are more likely to trust and to follow algorithmic advice than human advice, when faced with similar contradicting external evidence. (automation bias)

$H_2$ - We expect this tendency to be more emphasized the more participants perceive algorithms as superior to humans.

Selective Adherence to Algorithmic Advice

A second, diverging, concern regarding policy makers’ use of algorithmic advice is derived from the public administration behavioral work on policy-makers’ information processing. Building on motivated reasoning, this growing body of literature established that decision-makers tend to selectively interpret information and evidence in light of pre-existing stereotypes, beliefs and social identities. They assign greater weight to information that is congruent with their prior beliefs, and to contest inputs that contradict them (Baekgaard et al. 2017; Baekgaard and Serritzlew 2016; Christensen et al. 2018; Christensen 2018; James and Van Ryzin 2017; Jilke 2017; Jilke and Baekgaard 2020). These studies have demonstrated these tendencies with regard to the processing and interpretation of “objective” performance indicators. However, this has not been investigated yet in relation to algorithmic decisional aids.

Following a motivated reasoning logic, we would similarly expect decision-makers to adhere to algorithmic advice selectively, mainly when it matches their stereotypical view of the decision subject (rather than by default as expected by automation bias scholars). For example, we would expect judges or police officers to be more likely to follow or
adhere to an algorithmic risk assessment when it predicts a ‘high risk’ for a black defendant and ‘low risk’ for a white defendant and vice-versa. This theoretical expectation also corresponds to numerous studies demonstrating bureaucrats’ inclination to be affected in their decisions by stereotypes and accordingly to discriminate against minorities and disadvantaged groups (e.g. Jilke and Tummers 2018; Jilke, Van Dooren and Rys 2018; Pedersen, Stritch, and Thuesen 2018; Michener et al. 2020; Thomann and Rapp 2017; Andersen and Guul 2019; Olson 2016; Gilad and Dahan 2020; Assouline, Gilad and Ben-Nun Bloom, forthcoming).

Hence, extrapolating from this literature, we hypothesize that:

\( H_3 \) – Decision-makers are more likely to follow algorithmic advice that matches their prior beliefs and stereotypical views of the decision subjects. (selective adherence)

While public administration scholars have thus far not investigated concerns with selective processing of algorithmic outputs (or other algorithmic biases), it has been the subject of recent investigations by law and computer science scholars, in studies on the use algorithmic risk assessment by criminal courts (Green and Chen 2019a; 2019b; Stevenson 2018). However, we still lack theoretical understanding about the psychological micro-mechanisms underlying the selective adherence to algorithmic advice. Specifically, we do not know whether this tendency is specifically emphasized for algorithmic advice, or rather whether it applies equally to any policy advice (regardless whether algorithmic in nature or human cognition-based). In other words, are decision-makers more prone to selective adherence to algorithmic advice compared to equivalent human advice?

We could expect that algorithmic outputs may exacerbate the risk of selective adoption and discriminatory decisions. As noted earlier, literature on automation has theorized that automated decisional aids tend to create a “moral buffer”, acting as a psychological distancing mechanism resulting in a diminished sense of moral agency, personal responsibility and accountability for the human actor “because of a perception that the
automation is in charge” (Cummings 2006, 8). This feelings of moral and ethical disengagement and decreased responsibility and accountability may reduce decision-makers’ awareness of potential biases and implicit prejudice. Or worse: the algorithmic advice could vindicate and give free license to decision-makers’ latent views (racial, xenophobic, misogynistic, etc.) by providing them with a seemingly legitimate reason to adopt discriminatory decisions. Algorithms, in other words, could serve to ‘give permission’ to decision-makers to act on their biases: Algorithms’ face-value ‘neutral’ or ‘objective’ character would fend-off potential suspicions of bias and/or confirm the validity of biased or prejudiced decisions. An algorithmic recommendation aligned with decision-makers own biases could amount to a powerful (mathematical!) endorsement thereof. We therefore expect biased adherence to become especially emphasized for algorithmic (as opposed to human advice). Consequently, we further hypothesize that:

\[ H_4 – Selective adherence is more likely to occur when decision-makers receive an algorithmic rather than a human advice. \]

**Empirical Evidence from Previous Studies**

The question of how public policy-makers are influenced in their decisions by algorithmic advice has not been empirically examined in public administration research. Rather, the only existing peer-reviewed empirical studies on this topic to date are from law and computer science scholars, which have predominantly focused on the use of algorithms in pre-trial criminal judicial decisions in the US. As such, these studies stem from the underlying concern with high levels of detention in the US and its growing carceral state, and are aimed at investigating the promise of algorithmic risk assessment to decrease detention levels, through improving the accuracy of judges’ assessments of defendants’ recidivism risk. Their tentative findings, as detailed below, point at patterns consistent with selective, rather than automated, adherence.
Stevenson (2018) uses archival data of criminal cases from the state of Kentucky to compare observationally pre-trial detention rates before and after a reform in 2011 that made risk assessment mandatory in pre-trial procedures. She finds that the expansion in the use of risk scores led to an overall increase in pre-trial release immediately following the implementation of the reform, which can be attributed to judges’ greater reliance on the risk scores. However, the increase has eroded and almost disappeared within a matter of years as “as judges returned to their previous bail-setting practices” (p. 309).¹ This study further finds that, on average, judges were more likely to accept low scores for white defendants, while overriding similar scores for black defendants, leading to a greater increase in release rates for white suspects.²

The influence of recidivism risk scores on judges’ decisions was also examined by a series of experimental studies among laypersons, conducted by computer science scholars (Green and Chen 2019a, 2019b; Grgić-Hlača et al. 2019). The main part of these studies similarly includes a judicial decision-making task, in which participants (recruited via MTurk and Prolific) are shown details and descriptions of real arrests and are asked to predict the defendants’ recidivism risk, and participants’ predictions with/without an algorithmic risk assessment are compared. Grgić-Hlača et al. (2019) used a within-subjects design, in which they compared participants’ recidivism predictions before and after they view the algorithm-based prediction. They find that the participants did not significantly change their decisions, even when they receive feedback about the high accuracy of the algorithmic advice or are incentivised to make correct predictions. Green

¹ She estimates, in a subsequent not yet peer-reviewed publication (Stevenson and Doleac 2018), that Kentucky judges diverted from the advice of the risk assessment in about two thirds of all cases.
² Stevenson notes that the increased racial disparities could be explained by differences across the state counties, and hence she is cautious about this finding. An additional working paper by Albright (2019), which similarly analyzes data from Kentucky, is more confident about it. Applying more sophisticated time-series models accounting for variation across judges and counties, Albright concludes that the risk scores did actually increase racial disparities, and that “judges are more likely to override the recommended default for moderate risk black defendants than similar moderate risk white defendants” (p. 1). An additional working paper by Cowgill (2018) also finds observational evidence of judges’ selective adherence to algorithmic risk assessment scores. Analyzing data from Florida’s Broward county, he finds that receiving a medium versus low risk algorithmic score increased detention rates among black defendants, but not among white defendants.
and Chen (2019a, 2019b) further compare between black and white defendants, and indicate a *selective adherence pattern*: participants adhered to the algorithmic advice to a greater degree when it predicted either high risk for a black defendant, or low risk for a white defendant.

All in all, while most of these studies demonstrate that public decision-makers (i.e. judges in all these cases) can be affected in their decisions by algorithmic decisional aids, they do not provide particularly strong evidence for decision-makers’ automatic adherence to algorithmic advice, as expected based on automation bias literature. They provide instead tentative empirical evidence that decision-makers tend to process such advice in a biased, selective, manner: they seek to align the content of the advice with their prior stereotypical view of the decision subjects, and to adopt it selectively.

Still, these studies have several important limitations. *First*, while the aim of these studies was to learn about the influence of algorithmic decisional aids, their comparison was only to a condition where decision-makers did not receive any advice at all, as opposed to a comparable human expert advice. It is questionable, therefore, whether the effects found are attributed to algorithms *per se*, or rather that other professional advice that similarly includes numeric outputs would yield the same outcome. We propose that in order to isolate the distinct effect of algorithms, the appropriate counterfactual should be an equivalent numeric advice that is produced by a human expert. *Second*, we argue that these studies are ill-equipped to investigate decision-makers’ adherence to algorithmic advice (automation bias), since they lacked additional contradictory evidence or inputs from other sources. Rather, automation bias can be tested more effectively by supplementing the algorithmic advice with such additional inputs, a condition which ‘forces’ decision-makers to choose whether to rely on the automated authority or rather to take into account additional information sources and indicators. A similar approach was applied by previous automation bias experimental studies, where participants were given automated aids not aligned with other indicators (Skitka et al. 2000; Mosier et al. 1998; Skitka, Mosier, and Burdick 1999; 2000). *Third*, these studies did not examine decision-makers’ perceptions about the inherent superiority of computer algorithms as a potential
moderator of automation bias, as suggested by the psychology literature. And fourth, all these studies are focused on the application of algorithms in one specific policy context, in one country. It is important to explore the generalizability of these patterns to additional public policy areas, specifically given the rapid spread of algorithms across various policy contexts and jurisdictions.

Below, in the methodology section, we present our unique research design, and discuss how it overcomes these limitations.

**Research Design**

To examine our hypotheses, we designed and conducted two unique pre-registered survey experiments among 1,509 Dutch respondents, recruited from a large international online panel – Dynata (formerly “ResearchNow SSI”). Study 1 (N=605) was designed to test our automation bias hypotheses. Study 2 (N=904) was designed to replicate study 1 on a separate sample, as well as to test our hypotheses regarding selective adherence to algorithmic advice.

To clarify, our initial methodological choice to use a sample of laypersons is driven by practical and ethical considerations, as our theory applies to decision-makers, rather than to citizens. Still, we account for the inherent limitation of this choice and mitigate it by designing a realistic administrative decision-making task that does not require a specific professional background to complete – local school board decisions on the employment of teachers, given that in the Netherlands members of such boards are not required to complete a specific professional certification, and can be composed, among others, of volunteers such as parents (OECD 2014, 14). As elaborated below, we utilized a hypothetical scenario of an algorithmic performance evaluation tool, used as a decisional aid for the assessment of Dutch high-school teachers. Our decision to focus on this policy setting was inspired by the real-life case of Sara Wysocki – a math teacher in the US that was fired based on the advice of an algorithmic score (generated by a third-party), while ignoring her favorable record and reputation as a high-performing teacher (Turque,
Washington Post 2012, “‘Creative ... motivating’ and fired”). Wysocki’s story is often mentioned as an illustrative example as to dangers of bureaucracies’ reliance on black-box algorithms (O’Neal 2017). It arguably illustrates automation bias – the managers adhered to the advice (and were disinclined to scrutinize it), despite the availability of clear contradicting evidence and warning signs.

Accordingly, our initial aim was to simulate a similar scenario in which officials are required to make a decision of whether or not to extend the employment contract of a teacher, when an algorithmic score indicates that she performs poorly, yet additional evidence suggests otherwise. We apply this scenario to the Dutch context and test, experimentally, whether participants (online panelists) are more inclined to adhere to such an advice by an algorithm, compared to a human-expert, as expected by our automation bias hypothesis. We also examine, observationally, whether participants who perceive algorithms as having greater capacities than humans are more likely to defer to such algorithmic advice. In other words, in line with automation literature, we attempt to unearth the underlying mechanism potentially driving such deference patterns. In study 2, we further examine whether participants are more likely to follow such advice when it concerns a teacher from an ethnic minority, and whether respondents do so to a greater extent when the advice comes from an algorithm (as opposed to a human expert). Study 2 allows us to explore instead patterns of selective (rather than automatic) adherence.

As explained above, the main advantage of our choice of empirical setting is the fact that it involves a bureaucratic task that can be more easily exercised in a vignette survey experiment with laypersons (as opposed to decisions on criminal procedures, which require specific experience and expertise). This enables us to mitigate the inherent concern to the study’s external validity. Moreover, this setting concerns a high-stakes, life changing decision (termination of employment), an element which is key to our theory of policy-makers’ processing of algorithmic advice and as such relevant for similar high-stakes areas. The relevance of our chosen empirical setting further stems from the growing use of algorithms as decisional aids for personnel management tasks in education (Ross and Walsh 2019), as well as in other public policy domains (Engstrom et
al. 2020, see Eggers et al. 2019, Leicht-Deobald et al. 2019 for such applications also in the private sector). To the best of our knowledge, ours is the first study to empirically test the influence of algorithms in this significant context.

We tailored our survey experimental design to the Dutch context. In the Netherlands, all schools operate under publicly funded educational associations, which enjoy a large autonomy in their management. Important decisions, including personnel management and the employment of teachers, are made by a school board, which includes representatives of the educational association. In our study, as detailed below, we invite participants to a simulation task where they act as board members of a hypothetical Dutch high school (as appointees of the educational association), and they are asked to make decisions about the employment of three new teachers on a temporal contract (i.e. to permanently hire them or not). It is noteworthy that school board members in the Netherlands are not required to obtain a specific professional background, which enhances the reliability and relevance of our simulation task (among laypersons). Furthermore, to ensure the reliability and authenticity of our experimental simulation task, we consulted about the design with Dutch high school teachers (as well as Dutch colleagues), and pilot tested it among 300 Dutch participants before conducting the experiment. Indeed, participants’ qualitative comments to the questionnaire indicate that they perceived the simulation task as fairly realistic and took it seriously.

**Study 1: Automatic Adherence to Algorithmic v. Human Advice (Automation Bias)**

As mentioned, this study is designed to examine our hypothesis that decision-makers are inclined to over-trust algorithmic advice – i.e. to follow algorithmic predictions despite additional contradicting evidence, and to do so to a greater extent than when presented with an advice by human expert (H1). We also tested whether this tendency is exacerbated among respondents that assign higher performative capacities to these
algorithms (H$_2$). We pre-registered the study and administered it in February 2020.$^3$ The survey experiments were hosted on Qualtrics, and participants (N=605) were recruited through a large international online panel – Dynata (formerly “ResearchNow SSI”).$^4$ The survey was conducted in Dutch.

At the beginning of each survey, participants are informed that they would be asked to act as board members of a hypothetical Dutch high school (named “Talentum Lyceum”). To enhance the reliability of the scenario, we first provide them with general details about the school, such as the number of students, teachers, school budget etc. To disguise our actual focus on the use of algorithms, participants are first asked to perform a short task that regards setting the school’s strategy for the upcoming year, and then they are presented with the main experimental task. In the main task, we asked participants to make a decision regarding the employment of three teachers, which were hired the previous year for a trial period. We explain to the respondents only two of the three new teachers can be permanently hired, and accordingly they must choose one teacher to be fired (to be exact – for her contract not to be renewed). As a basis for their decision, participants are given two data inputs (one qualitative input, and one numeric input – a score) per each teacher in both the algorithmic and the human advice condition. In the algorithmic condition, respondents are told the score input is produced by an algorithm, while for the human advice condition that it is produced by human expert.

More precisely, the first input, which was identical for all participants, is a brief summary of a qualitative evaluation by the HR person of the educational association. The second is a numeric prediction of teachers’ potential to perform well in the future, ranging between 1 (lowest) to 10 (highest). Participants are told that this evaluation was conducted by an external consultancy company named ILE (short for Innovatieve Lerarenevaluatie –

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$^3$ The pre-registration form of study 1 is available at [http://aspredicted.org/blind.php?x=rj829d](http://aspredicted.org/blind.php?x=rj829d). [anonymized during the peer-review]

$^4$ We started with 910 observations, of which we filtered out 305 participants who failed IMC test or filled the questionnaire in less than 3 minutes. We initially aimed at a sample of 600, for which an effect size of OR=1.5 (50% increase) is detectable with power of 0.7 (p = 0.05, one-sided test), and OR=1.63 is detectable with power of 0.8.
“Innovative Teacher’s Evaluation”), and accordingly we refer to it as the “ILE evaluation score”. Respondents are randomly assigned to one of two conditions: they are either told that the ILE score is produced by a Machine-Learning algorithm\(^5\) (algorithmic advice condition), or that it is produced by human consultants (human-expert advice condition). We kept the text structure and wording of these two conditions as equivalent as possible. Also, to bolster participants’ confidence in the predictive capacity of the ILE score, we noted (in both conditions) that it “was proven highly effective in predicting teacher performance, with an accuracy rate of 95%”. The full texts of the two conditions are presented in APPENDIX A (translated from Dutch).

It is noteworthy that the format that we used for the ILE evaluation score (an integer number between 1 and 10) was designed to resemble the COMPAS risk score that is used in pre-trial procedures across the US. Likewise, the additional qualitative evidence about the teachers in our experimental task (the HR person’s evaluations) can be compared to the additional qualitative evidence about the defendants that is delivered to a judge to inform his/her decision, alongside the COMPAS algorithmic risk score, which similarly ranges from 1-10.

Participants were then shown a table that presents the three teachers and the two inputs for each teacher (see Figure 1 below). In line with our theoretical focus, we deliberately designed the task so that there will be an incongruence between the two inputs in the table: the lowest ILE score (4) is never matched with the most negative qualitative HR evaluation.\(^6\) Accordingly, participants faced a decision of whether or not to follow the

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\(^5\) This is a popular subset of artificial intelligence algorithms that self-learn from data.

\(^6\) The incongruence was as follows: One of the three teachers received a relatively low ILE score of 4, whereas the other two received scores of 8 and 6. The HR person’s qualitative evaluation similarly varies as one of the three teachers gets negative remarks (e.g. “she does not meet the standards for a teacher in this school”), whereas the other two teachers receive positive and respectively, mixed evaluations. Most importantly however, the negative qualitative evaluation is not assigned to the teacher with the lowest ILE score (4), but to one of the other teachers. Instead, the teacher with the low ILE score receives positive or mixed qualitative evaluations. For exploratory purposes, we also randomly assigned participants to several conditions of incongruence, ranging from high (where the teacher with the lowest ILE score is the one with the most favorable qualitative evaluation) to more modest (where the teacher with the lowest ILE score is the mixed qualitative evaluation). We did not find significant differences in our outcome variable across
“advice” of the ILE score (i.e. to fire the teacher with the most negative ILE score), given its incongruence with the HR person’s qualitative evaluation.

In other words, through the qualitative input (HR evaluation), respondents in both conditions receive informational cues that are at odds with the ILE score. We coded our outcome variable 1 in case participants choose to fire the teacher with the lowest ILE score, and 0 otherwise. To minimize additional differences in the characteristics of the three teachers, which could potentially affect participants’ decisions, we used three female teachers, all of whom have typical Dutch names, and their teaching areas are in natural sciences.

these conditions, and there is no interaction between them and our main manipulation. Hence, in the paper, we do not account for these differences. In addition, in study 1, the order of the three teachers was randomized, with no significant differences on participants’ decisions. In study 2, all participants received the teacher in the order presented in the Figure 2, i.e. from best assessment to worst.
Figure 1: Experimental Task

| Teacher: | 1. A. Verhagen (Chemistry) | 2. M.S. Jansen (Biology) | 3. F.E. den Heijer (Physics) |
|----------|----------------------------|--------------------------|-----------------------------|
| 1. Assessment by Human Resources person: | The quality of Ms. Verhagen's teaching is excellent and her classes have performed very well in the central exams. She is also highly appreciated by the other teachers, the students and the parents. I believe she has a high potential as a teacher. | The average scores of Ms. Jansen's classes in recent central exams are somewhat below the national average. On the other hand, she has a high motivation, she did manage to make some improvement along the year. Overall, I believe that she has potential, yet she still has to make much progress. | The scores of Ms. Heijer's classes in national exams are well below the national average. Also, she does not seem motivated and it doesn't seem there has been much improvement in her teaching throughout the year. Overall, she does not meet the standards for a teacher in this school. |
| 2. [Consultants/ Machine learning algorithm] evaluation score (ILE): | 4 | 6 | 8 |

| Evaluation score by ILE [consultants / machine-learning algorithm]: |
|---|---|---|---|---|---|---|---|---|---|
| Lowest potential | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| Highest potential |

Whose contract would you recommend not to renew? To reiterate, you are requested to choose 1 teacher.

The main task was followed by a series of manipulation check questions, to confirm that participants were aware of the source of advice (algorithmic/human) as well as of the ILE score. Around 75% of participants remembered the type of advice (algorithmic v. human) and a similar percentage remembered the ILE score of the teacher which they chose to fire, with no significant differences between the algorithmic and human-expert conditions. In our robust analyses, which we report below, we restricted our sample to those who answered these questions correctly. We also asked participants in this section
to indicate whether the qualitative evaluation of the selected teacher was better or worse than the others, and almost 75% of them answered that question correctly. These manipulation checks are reported in details in the online appendix.

Thereafter, we asked participants a battery of questions about the process by which they made their decision, and we asked them to reflect on this process via an open question. This section was followed by an instructional manipulation check. We then asked the participants assigned in the algorithmic advice condition several additional questions regarding their perceptions of algorithms and specifically their superiority to humans. The latter variable, which was relevant for our second hypothesis, is measured through the following three Likert-scale items: “Algorithms take into account more information than humans”; “Algorithms make better judgments than humans on most tasks”; “In judgments that concern other people, algorithms make fairer judgments than humans” (Cronbach $\alpha = 0.74$, factor scores above 0.58). The two first items are adopted from Skitka et al. (2000), to which we added a third item that accounts for the fairness dimensions which is key to the context of public policy. Finally, all participants were asked a battery of demographic questions.

In our analyses below, we compare participants’ likelihood of following the ILE score between the two conditions (algorithmic v. human-expert), to test the automation bias hypothesis. Also, we test our second hypothesis, observationally, through regressing our outcome variable on the three items that account for the perceived performative capacities of algorithms (among the subset of the algorithmic advice condition). Ideally, we would have also collected data about this latter variable for the human-expert condition, and confirm that it is indeed correlated with following the algorithmic ILE score, but not with the human-based ILE score. Doing so presented however, bigger validity threats to the study, which lead us not to do so.\footnote{While we considered this option when designing the survey, we decided eventually to include these post-manipulation questions only for those in the algorithm condition, for two main reasons: First, adding these questions to the human-expert group would be completely out of the survey context for that group, and second, such comparison between the groups, whereby one is already primed with an algorithmic advice while the other is not, is flawed. An additional option would be to ask these questions before the random}
theoretical reason why people’s perceptions of algorithms would have a direct positive influence on their tendency to adhere to advice by a human-expert, one can argue that this variable is confounded by other variables, which would affect the outcome variable under both conditions. To address this concern, in our analyses we also control for demographic variables that potentially confound this effect.

_Study 2: Selective Adherence to Algorithmic v. Human Advice_

This study is designed to replicate the results of study 1 as well as to test the additional hypotheses that decision-makers are more inclined to follow algorithmic advice inasmuch as it is aligned with their stereotypical views of the decision subjects (H3), and that this selective pattern is more pronounced for AI algorithms compared with human experts (H4). We pre-registered the study and administered it mid-March 2020, and recruited participants similarly through Dynata (N=904).8

In this study, we repeated the abovementioned procedure of study 1, while adding a manipulation of teachers’ names as a cue for their ethnic background of Dutch versus Moroccan. The control condition is identical to study 1 – all three teachers are given typical Dutch surnames (“Verhagen”, “Jansen” and “den Heijer”). In the treatment condition, the name of the teacher who received the lowest ILE score (4) is changed to “El Amrani”, a common surname for Dutch citizens of a Moroccan background.9 We specifically selected this ethnic minority group in the Netherlands, since it is a minority group that is often negatively stereotyped (Jilke, Van Dooren and Rys, 2018; Kamans et

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8 The pre-registration forms of study 2 is available at [http://aspredicted.org/blind.php?x=2vk2a8](http://aspredicted.org/blind.php?x=2vk2a8). [anonymized during the peer-review]. Applying similar filtering methods, we screened out 415 observations of our raw sample of 1,222.

9 In the first wave of our data collection for study 2, we included additional conditions where the Moroccan name “El Amrani” is assigned to one of the other teachers, who did not receive the lowest ILE score. We then decided, in line with our theoretical focus, to remove from our analyses the observations of these additional conditions (n=316), and to continue the data collection without these conditions. In the online appendix we add these observations to our analyses of our automation bias hypotheses, with no significant change to the results.
In our analyses below, we examine the effect of this manipulation on participants’ inclination to follow the ILE score, and its interaction with the type of advice (algorithmic v. human-expert). For these analyses, we further filtered our sample and kept participants who are of Dutch descent (n=792). Yet, we used the entire sample of 904 for the replication of the findings of study 1. It is important to note that previous vignette survey experimental studies (as opposed to field experiments) have frequently failed to identify discriminatory patterns, which has been explained by social desirability pressures and the difficulty of simulating the conditions of real-world decision-making (Wulff and Villadsen 2020). We were certainly aware of this limitation when designing our study, and for this reason we argue that our study can be considered as a particularly hard case for our selective adherence hypothesis.

The overall experimental design of the two studies and the number of respondents in the different conditions is illustrated in Figure 2. The main characteristics of our samples are summarized in APPENDIX B, and the full survey is available in the online appendix.11

Figure 2: Experimental design

![Figure 2: Experimental design](image)

Note: In Study 2, the sub-samples of the teacher’s ethnic background include only the participants of Dutch origin (n=792).

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10 We initially sought to collect 600 observations, and to increase our sample if necessary. Eventually, after reaching 600 and filtering the data, we decided to aim at 800 observations for these analyses, and accordingly increased the total sample to 900.

11 Replication materials would be available online.
Results

Based on our first hypothesis, and in line with automation bias literature, we expected the probability of following the advice of the ILE score to be significantly higher among those assigned to the AI algorithmic advice, compared to those receiving a similar prediction by human experts. In contrast with this expectation, in study 1, we find very small differences between these two groups (11.5% in the algorithmic condition v. 11.9% in the human-expert condition). Indeed, under both conditions, the vast majority of participants chose to override the ILE score, and instead preferred to fire (not renew) the teacher with the poorest qualitative evaluation.\(^\text{12}\) In other words, contrary to automation bias expectations, respondents did not automatically adhere to the algorithm, ignoring contradictory information from alternative sources (in our case the qualitative evaluation). We further replicated these analyses with regard to the sample of Study 2 (\(N=904\)). The differences are in the expected direction, yet they are still relatively small (10.8% v. 9.5%).

We further analyzed the effect of our manipulation of algorithmic versus human advice via logistic regression analyses, presented in Table 1. In Models 1.1 and 1.2 we regress our binary outcome variable on the advice manipulation among the two studies, separately, and thereafter in Model 1.3, we combined the two samples (\(N=1,509\)). The combined sample is sufficiently powered to detect an effect size equivalent to a 36% increase in the probability of following the ILE score, an effect size which is generally considered a small-size effect (Chen, Cohen, and Chen 2010).\(^\text{13}\) Finally, in Models 1.4 and 1.5, we further tested the robustness of these findings by restricting our combined sample to those who completed our manipulation checks as well as by controlling for demographics, with no major changes to the results. The effect of receiving an advice from an algorithm (compared with a human-expert) is statistically insignificant in all these analyses.

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12 79% of all participants selected the participants selected the teacher with the poorest HR evaluation.

13 Power=0.8, p=0.05 (one-sided test).
Overall, our experimental findings from the two separate studies do not reveal a general pattern of automatic adherence to algorithmic advice. Rather, they suggest that decision-makers do not tend to follow the default policy decision proposed by an artificial intelligence algorithmic decisional aid much more than they would for human expert advice. Certainly, we cannot completely rule out the possibility that people are more likely to follow an algorithmic than a human expert advice in our experimental setting (i.e. type II error). Yet, given our large sample from the two studies, we argue that we are able to infer with sufficient confidence that even if such an effect exists – that averaged treatment effect is at best of a relatively small size.

**Regression Table 1**

| Predictors | Study 1 (1.1) | Study 2 (1.2) | Combined (1.3) | Combined (robust samples) (1.4) | Combined (1.5) |
|------------|---------------|---------------|----------------|----------------------------------|----------------|
| Algorithm  | 0.96          | 1.16          | 1.07           | 1.08                             | 1.10           |
|            | (0.58–1.58)   | (0.75–1.80)   | (0.77–1.48)    | (0.67–1.73)                      | (0.79–1.53)    |
| Female     | 0.75          | 0.75          | 0.75           | 0.75                             | 0.75           |
|            | (0.52–1.06)   | (0.52–1.06)   | (0.52–1.06)    | (0.52–1.06)                      | (0.52–1.06)    |
| Age        | 1.00          | 1.00          | 1.00           | 1.00                             | 1.00           |
|            | (0.99–1.01)   | (0.99–1.01)   | (0.99–1.01)    | (0.99–1.01)                      | (0.99–1.01)    |
| Income     | 1.20          | 1.20          | 1.20           | 1.20                             | 1.20           |
|            | (1.06–1.36)   | (1.06–1.36)   | (1.06–1.36)    | (1.06–1.36)                      | (1.06–1.36)    |
| Intercept  | 0.14          | 0.10          | 0.12           | 0.09                             | 0.11           |
|            | (0.09–0.19)   | (0.08–0.14)   | (0.09–0.15)    | (0.06–0.13)                      | (0.09–0.14)    |
| N          | 605           | 904           | 1509           | 883                              | 1495           |
| log-Likelihood | -218.769   | -297.144     | -516.535      | -258.982                         | -508.089       |

**Note:** In all our regression tables, p-values refer to a two-sided test. Predictors are centered at their grand mean. Regression Tables produced via sjPlot R package (Lüdecke 2020)
We further explored the differences between the two groups in their self-reflections of the decision making process. While there were no significant differences in their likelihood of following the advice, as outlined above, we find that participants in the algorithmic advice reported giving significantly less weight to the ILE score in their decision (Diff = 0.453 CI[0.292, 0.615] on a 1-7 Likert scale, $t = 5.522, p < 0.001$), and more weight to the HR person’s qualitative evaluation (Diff = 0.122 CI[-0.005, 0.249] on a 1-7 scale, $t = 1.883, p = 0.06$). Moreover, when asked to describe in their own words “the thought process that led to [their] decision”, many of the respondents in the algorithmic advice group stressed their discomfort with the use of algorithms, and mentioned their inherent limitations in evaluating human interactions and susceptibility to manipulation. While these patterns are not reflected in the decision outcomes, they suggest that participants tend to perceive algorithmic predictions as less “authoritative” than human-expert inputs, contrary to our expectation based on automation bias theory.

Next, and following these latter insights, we tested the relation between people’s perceptions of algorithms’ superiority to humans and their tendency to adhere to their advice (i.e. our second hypothesis). As explained above, we measured this variable directly in our survey via a composite index of three items shown to the respondents in the algorithmic advice condition. The index of perceived superiority of algorithms ranges between 0 to 1, where higher values indicate greater superiority of algorithms. Figure 3 shows the distribution of this variable among the combined sample of the two studies. Overall, as shown by this figure, participants in our sample vary greatly in their perceptions of the algorithms’ capacities, with slightly more participants viewing algorithms as having relatively greater capacities than humans (43% of the participants have scores higher than the scale’s middle value, compared with 37% who have scores lower than the middle value). There were no significant mean differences between the two studies in relation to that variable.
The probability for compliance with the algorithmic ILE prediction (our outcome variable) was more than double among those participants who have an index score higher than 0.5 (the scale’s middle point), compared with those with a score lower than 0.5 (15.7% versus 7.2%). The probability among those with a score higher than 0.75 was particularly high, and reached 22.6%. Table 2 presents our logistic regression models with our perceived algorithmic superiority index as an independent variable. *Perceived superiority of algorithms* has a positive and statistically significant effect on our outcome variable. This positive effect increases further when we restrict the sample to those who passed the manipulation checks (Model 2.2), and it remains when controlling for participants’ gender, age and level of income (Model 2.3). In Figure 4, we graphically illustrate our prediction of Model 2.3, along with the actual probabilities in our data.\(^\text{14}\)

Hence, while our experimental examination did not reveal a clear general pattern of automatic adherence to algorithmic advice, our observational survey data suggests, in line with our second hypothesis, that algorithms tend to be highly influential for those decision-makers who perceive algorithms *a priori* as being superior to humans in their

\(^{14}\) We present analyses for the combined sample, due to the relatively small samples of the separate studies. The coefficient is positive in both studies, yet it is greater in the second study.
performative capacities. We find that those who hold such with favorable views of algorithms are much more likely to follow an algorithmic advice against contradicting evidence. Moreover, given that this effect is not confounded by demographic variables, it is relatively safe to conclude that such people are not likely to follow in the same manner an advice by human experts.

**Regression Table 2**

| Predictors                        | Combined (2.1) | Combined (robust sample) (2.2) | Combined (2.3) |
|-----------------------------------|---------------|---------------------------------|---------------|
| Perceived superiority of algorithms | 6.97 (1.97–25.46) | 35.22 (4.53–307.14) | 5.56 (1.59–20.06) |
| Female                            | 0.62 (0.38–1.00) | -1.93 | 0.053 |
| Age                               | 0.62 (0.99–1.02) | 0.50 | 0.617 |
| Income                            | 1.15 (0.97–1.38) | 1.58 | 0.114 |
| Intercept                         | 0.12 (0.09–0.15) | -17.59 <0.001 | -0.08 (0.06–0.12) | -13.15 <0.001 |
| N                                 | 754 | 449 | 748 |
| log-Likelihood                    | -258.895 | -128.884 | -253.724 |
Figure 4: Model Prediction

Note: Lines represent prediction ad 95% CIs, based on Model 2.1. Blue dots represent descriptive probabilities in our dataset. Dots’ size represents the number of participants.

We now turn to discuss the results of our second study in relation to our hypotheses of selective adherence. To reiterate, in study 2 we further experimentally tested whether participants were more likely to fire the teacher with the lowest ILE score, when this teacher is identified as a member of a stereotyped ethnic minority group – in our case, Moroccan (H3). Our sample testing this hypothesis therefore was filtered to include only respondents of Dutch descent. In addition, our 2×2 factorial design enables us to compare the effect of the random assignment (Moroccan/Dutch teacher) across the different types of advice (algorithmic versus human-expert), putting to rigorous experimental test the hypothesis that algorithms (compared to similar human advice) exacerbate this pattern of selective adherence and enhance group disparities (H4).

Table 3 includes the results of our regression analyses for these two hypotheses. In Model 3.1, we regressed our outcome variable on the two manipulations, and thereafter in Model 3.2 we add their interaction. Then, similarly to our previous tables, in Models 3.3 and 3.4 we replicate our model on our robust sample, and add additional controls. Recall that in all these analyses, we limited our sample to participants of Dutch origin.
We find a main effect for the “Moroccan teacher” manipulation, in the expected direction. A Moroccan teacher with a low ILE score is 50% CI[-5%–140%] more likely not to have their contract renewed, compared to a Dutch teacher with the same score (Model 3.1, p=0.042, one-sided test), and this effect survives our additional tests of controlling for covariates and filtering out those who did not properly read the task. Descriptively, 12.3% of the participants who were presented with a Moroccan teacher chose to fire her, compared with 8.6% of those who were shown a Dutch teacher. Given established difficulties for survey experimental designs to identify such discriminatory patterns, it is safe to assume that the effect size is greater in real-world decision-making settings.

As for the interaction between the Moroccan teacher condition and the algorithmic advice condition, it is not statistically significant in any of our interaction models (3.2-3.4), by contrast with our H4. Hence, while we do find evidence that participants are more inclined to follow the ILE score when it matches the stereotypical view of that teacher, our findings do not suggest that this bias is increased when the score is produced by an algorithm. If anything, the direction of the interaction terms in our models are consistently negative (OR = 0.50 CI[0.19–1.27] in Model 3.2). Descriptively, the differences between the Moroccan and Dutch teacher in the human-expert advice group were 6.7% (12.9% versus 6.2%), compared with 1% in the algorithmic group (11.6% versus 10.6%).

15 In other models, we further tested the interaction between the Moroccan teacher manipulation and participants’ answers about the performative capacities of algorithms. These interactions are positive, but not sufficiently significant (OR=1.34, p=0.285).
Regression Table 3

| Predictors                  | Study 2  | Study 2  | Study 2 (robust samples) | Study 2  |
|-----------------------------|----------|----------|--------------------------|----------|
|                             | (3.1)    | (3.2)    | (3.3)                    | (3.4)    |
| **Algorithm**               |          |          |                          |          |
|                             | 1.20     | 0.78     | 1.80                     | 1.80     |
|                             | (0.76–1.91) | 0.438   | (0.88–3.83)              | 0.114    |
|                             |          |          | 1.185                    | 1.17     |
|                             |          |          | (0.68–5.53)              | 0.241    |
|                             |          |          | 1.85                     | 0.91     |
|                             |          |          | (0.91–3.96)              | 1.65     |
|                             |          |          | 0.099                    |          |
| **Moroccan teacher**        |          |          |                          |          |
|                             | 1.50     | 1.73     | 2.23                     | 2.19     |
|                             | (0.95–2.40) | 0.083   | (1.11–4.73)              | 0.029    |
|                             |          |          | 2.24                     | 1.55     |
|                             |          |          | (0.84–6.63)              | 0.120    |
|                             |          |          | 2.25                     | 2.25     |
|                             |          |          | (1.11–4.80)              | 2.20     |
|                             |          |          | 0.028                    |          |
| **Algorithm x Moroccan teacher** |          |          |                          |          |
|                             | 0.50     | -1.45    | 0.42                     | -1.25    |
|                             | (0.19–1.27) | 0.147   | (0.10–1.60)              | 0.211    |
|                             |          |          | 0.49                     | -1.46    |
|                             |          |          | (0.18–1.26)              | 0.144    |
| **Female**                  | 0.72     | -1.25    | 0.72                     | -1.25    |
|                             | (0.43–1.20) | 0.212   | (0.43–1.20)              | 0.212    |
| **Age**                     | 1.00     | -0.52    | 1.00                     | -0.52    |
|                             | (0.98–1.01) | 0.602   | (0.98–1.01)              | 0.602    |
| **Income**                  | 1.19     | 1.92     | 1.19                     | 1.92     |
|                             | (1.00–1.41) | 0.055   | (1.00–1.41)              | 0.055    |
| **Intercept**               | 0.08     | -11.16   | 0.07                     | -9.10    |
|                             | (0.05–0.13) | <0.001 | (0.03–0.11)              | <0.001 |
|                             |          |          | 0.05                     | -7.01    |
|                             |          |          | (0.02–0.11)              | <0.001 |
|                             |          |          | 0.19                     | -9.19    |
|                             |          |          | (0.03–0.11)              | <0.001 |
| **N**                       | 792      | 792      | 473                      | 791      |
| **log-Likelihood**          | -261.789 | -260.719 | -133.314                 | -257.122 |

To summarize, with regards to *selective adherence* (study 2), we did find evidence that participants tend to follow both human and algorithmic advice recommendations in a *selective* manner – when it corresponds to pre-existing biases and stereotypes, which translates into group disparities (in support of our H3). However, our findings suggest that this bias is neither unique for algorithmic decisional aids, nor it is more pronounced for them. Rather, our analyses suggest that such selective processing patterns are probably similarly likely to be found for similar outputs produced by human experts.
Discussion and Conclusion: Automated Deference v. Selective Adherence to Algorithmic Advice

With AI set to fundamentally alter decision-making in public organizations (Young, Bullock and Lecy 2019), how do human decision-makers actually process algorithmic advice? Drawing on two separate strands of behavioral literature – social psychology studies on automation as well as extrapolating from extant BPA literature on information processing (non-algorithmic) – we set out to investigate two distinct sets of biases potentially associated with the use of algorithms as decisional aides in the public sector: automatic v. selective adherence to algorithmic advice.

We did not find evidence for decision-makers’ overall tendency for automatic deference to AI algorithmic advice (automation bias). Our experimental test for this pattern – a comparison between participants’ reliance on algorithmic and human-expert based advice, amidst contradicting evidence – did not yield significant differences between the two conditions. The vast majority of the participants in both groups chose to override the prediction score. Nevertheless, our observational data suggests that a tendency for automation bias does actually occur among those relatively few participants (at least for now) who perceive algorithms as superior to humans.

While we did not find evidence for automation bias, at least in relation to the majority of the population, we did find strong support for selective adherence. An important (and disconcerting) finding of our study is that algorithmic outputs are processed in a biased way by human decision-makers, which may result in greater discrimination. We find that decision-makers are more likely to defer to an algorithmic advice when it is aligned with their pre-existing stereotypes. These patterns, which are in line with the findings of previous studies on pre-trial algorithmic risk scores by law and computer science scholars respectively (Stevenson 2018, Green and Chen 2019a, 2019b), are fairly robust in our experimental study. Moreover, given established difficulties for survey experimental designs to identify such discriminatory patterns, the effect size is likely greater in real-world decision-making settings. Our findings also suggest that the bias is not more severe
for algorithmic advice when compared to human advice, as the interaction between the two manipulations is insignificant. This suggests that the tendency for selective adoption is not specifically linked to the unique nature of algorithms, as theorized.

A key concern stemming from automation studies is that decision-makers would automatically default to the algorithm, potentially then to poor algorithmic advice as well (ignoring contradictory informational cues). This becomes a growing concern in a context of well-documented algorithmic shortcomings and “machine bias” failures. We find that a tendency to defer to the algorithm, rather than generalized, is instead selective and more likely to occur when this advice matches pre-existing stereotypical beliefs. Bureaucratic deference to algorithmic advice (but not only) is more likely to disproportionately affect disadvantaged groups.

Our experimental findings – both in relation to the automation bias hypothesis and to the selective adherence hypothesis – are largely consistent with findings from earlier studies by legal scholars and computer scientists on pre-trial algorithmic risk scores in US context. These studies too did not reveal an overwhelming pattern of automatic adherence of decision makers (judges in their cases) to algorithmic risk scores. Rather, they demonstrated that they tend to follow these scores when predictions fit group stereotype-based expectations. An important limitation of these previous studies however, was that they failed to compare algorithmic advice with equivalent human advice. Our study advances current theoretical understanding of this bias, by demonstrating that the selection bias is not unique for algorithmic advice, and seemingly not more severe than for human advice.

Still, how can we reconcile the results of our study (and studies above) with findings from studies in social psychology on the use of automation in aviation and healthcare, where such patterns have been well-documented and recognized? One possible explanation for this discrepancy is (current) relative skepticism about the performative capacity of algorithms, and their perceived superiority to human experts. As noted above, and consistent with automation bias literature, we find higher rates of adherence to
algorithmic advice associated with this variable. A potential explanation for this skepticism might be related to the likely novelty of AI algorithm use in the public sector, with many citizens still under-exposed to it. This is an important difference to earlier studies on automation applied in areas well-acclimated to such devices (aviation, medicine), characterized by repeated and routine use of automation, resulting in high levels of trust in their performance. This contention is supported by the fact that most of the respondents in our sample (almost 80 percent) reported low awareness of the use of algorithms in the public sector – as such. In other words, they are not yet well-familiarized with algorithmic systems, nor did they have repeated exposure to their performative capacities.

Hence, we argue that it is too soon to rule out our concerns with automation bias in the context of the public sector use of AI. Rather, automatic deference to algorithmic advice in policy advice could become more prevalent as human decision-makers become increasingly exposed to algorithms and AI solutions in their public lives, as well as in the practice of public sector organizations. Repeated experience with high-performing AI systems might increase ‘user appreciation’ of their judgement capacities (decrease skepticism), leading to higher level of deference over repeated interactions. This is an important avenue, in our view, for future investigation.

Importantly, our findings of selective adherence contradict the ‘promise of neutrality’ that has propelled and fueled algorithm use in the public sector. This promise of neutrality has been a key justification for algorithms adoption in high stakes areas such as criminal justice and policing, and for ‘tolerating’ shortcomings of such systems (e.g. pertaining to their opaqueness and associated concerns with transparency and accountability) in the name of their superior performative capacities, allowing us to overcome human biases and limitations. The findings of our study belie this claim. Reliance on algorithmic advice in public sector decision-making does not completely remove human bias from the equation. While this is not a new observation when it comes to algorithms’ own learning and functioning (i.e. ‘machine bias’– algorithms replicating and propagating historical bias learned from training data – is a well-documented problem that can arise in
algorithm deployment), we find that bias also crops up at another stage: in the interaction between humans and algorithms, in how decision-makers process, interpret, and act upon algorithmic outcomes.

Our findings raise (in fact, add) serious questions about the added value of the reliance on algorithmic advice as a mechanism to avoid bias. Even assuming that the algorithmic outputs themselves can be bias-free, human decision-makers rely on such outputs selectively i.e. when the findings ‘suit’ pre-existing stereotypes. This is disconcerting: Keeping humans-in-the-loop (human intervention) is considered an important check on algorithmic failures (for instance, on issues of ‘machine bias,’ noted above) and is even legally-mandated to that end, in forward regulatory frameworks such as the EU GDPR. While our findings as to a lack of automatic deference are encouraging in this context, it appears however, that human decision-makers actually tend to adhere (rather than resist) to the algorithm precisely when the algorithm’s predictions are aligned with stereotypes and disadvantage minority groups. Such concerns would become especially problematic in mixed algorithmic decision-making when human bias meets algorithmic bias – human decision-makers, our study reveals, are potentially unreliable decisional mediators.

Our study also has important limitations that must be acknowledged. Our investigation pertains to a single public sector domain (education) and within it to a specific task, while our participants were laypeople rather than actual decision-makers. We attempted to mitigate this and maximize the external validity of our study through designing a task that can be completed by laymen, and what is more, is carried out in real-life scenarios in the absence of a professional certification, also, among others, by lay members. Future studies could test to what extent these findings are replicated in surveys with actual decision-makers, ideally operating in different policy areas and in relation to various tasks. Importantly, follow-up work could further test the role of repeat exposure for algorithm adherence through a design that allows for repeat interactions with the algorithm so as to assess to what extent participants’ trust in the algorithm increases over time, potentially leading, as we theorize above, to enhanced deference.
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APPENDIX A: Experimental task

The text below is a direct translation of the Dutch survey (available in the online APPENDIX). For the sake of accuracy, we did not alter the formulation of the translation for it to sound stylistically better in English but opted to stay as close as possible to the Dutch text.

***

[Algorithmic advice condition]
The ILE evaluation is generated by a machine-learning computer algorithm (a form of artificial intelligence) that uses various factors related to the background and functioning of teachers and estimates their potential to perform well in the future. The algorithm, based on a mathematical model, uses a large database and generates an individual score for each teacher, ranging between 1 (lowest potential) and 10 (highest potential).

Public organizations are frequently assisted by machine-learning algorithms for various tasks.

The machine-learning algorithm used by ILE was proven as highly effective in predicting teacher performance, with an accuracy rate of 95%.

[Human advice condition]
ILE evaluation is produced by its consultants, who examine various aspects related to teachers’ background and functioning. Based on this, the consultants assess their potential to perform well in the future. The consultants, relying on their professional knowledge and experience in the field, generate an individual score for each teacher, ranging between 1 (lowest potential) and 10 (highest potential).

Public organizations are frequently assisted by consultants for various tasks.

The evaluation method used by ILE consultants was proven as highly effective in predicting teacher performance, with an accuracy rate of 95%.
### APPENDIX B: Sample characteristics

|                         | Study 1 (N=605) | Study 2 (N=904) |
|-------------------------|-----------------|-----------------|
| **Gender**              |                 |                 |
| Men                     | 275 (45.5%)     | 471 (52.1%)     |
| Women                   | 329 (54.4%)     | 432 (47.8%)     |
|                         | 1 (0.2%)        | 1 (0.1%)        |
| **Age**                 |                 |                 |
| 18-25                   | 85 (14%)        | 156 (17.3%)     |
| 26-35                   | 87 (14.4%)      | 114 (12.6%)     |
| 36-45                   | 103 (17%)       | 116 (12.8%)     |
| 46-55                   | 107 (17.7%)     | 167 (18.5%)     |
| 56-65                   | 117 (19.3%)     | 193 (21.3%)     |
| 66-75                   | 82 (13.6%)      | 134 (14.8%)     |
| 75+                     | 13 (2.1%)       | 23 (2.5%)       |
|                         | 11 (1.8%)       | 1 (0.1%)        |
| **Income**              |                 |                 |
| 1. Far below average    | 155 (25.6%)     | 243 (26.9%)     |
| 2. Slightly below average | 112 (18.5%)   | 157 (17.4%)     |
| 3. Around average       | 138 (22.8%)     | 190 (21%)       |
| 4. Slightly above average | 134 (22.1%)   | 200 (22.1%)     |
| 5. Far above average    | 55 (9.1%)       | 113 (12.5%)     |
|                         | 11 (1.8%)       | 1 (0.1%)        |
| **Education**           |                 |                 |
| 1. Secondary education (VMBO/Havo/Vwo) | 131 (21.7%) | 212 (23.5%) |
|                         | 161 (26.6%)     | 237 (26.2%)     |
| 3. College high education (HBO) | 207 (34.2%) | 289 (32%)   |
| 4. University high education (WO) | 86 (14.2%) | 143 (15.8%) |
|                         | 20 (3.3%)       | 23 (2.5%)       |
Online appendix

Contents:

1. Manipulation checks
2. Supplementary analyses
3. Survey

1. Manipulation checks

In this section we report the results of our manipulation checks, which we included in the survey, immediately after the main task. For each manipulation check, we present the percentage of participants who answered the question correctly, across the two studies and the two conditions.

Our first check was aimed at confirming that participants were aware of the source of advice (algorithmic or human advice). We included the following question:

The ILE evaluation score is produced by
- A machine-learning computer algorithm.
- An assessment by consultants.
- An assessment by other teachers.
Our second check was aimed at confirming that participants have noticed the ILE score of the teacher they selected, as well as those of the other teachers. We included two questions:

What was the ILE evaluation score of [teacher selected]?

1 2 3 4 5 6 7 8 9 10
The evaluation score of [teacher selected] was:

- Higher (better) than the score of the other two teachers.
- Lower (worse) than the score of the other two teachers.
- Neither the lowest, nor the highest.

### % correctly answered the question

|       | Algorithm | Human |
|-------|-----------|-------|
| Combined | 65.3% | 64% |
| Study 1 | 64.7% | 61.6% |
| Study 2 | 65.7% | 65.7% |

Finally, we tested whether participants have noticed the HR person’s evaluation of the teacher they selected, as well as those of the other teachers. We included the following item:

The assessment by the HR person of [teacher selected] was:

- Better than the assessment of the other two teachers.
- Worse than the assessment of the other two teachers.
- Neither the best, nor the worst.
2. Supplementary analyses

In the tables below, we report the results of additional analyses.

Table A1 reports the descriptive results across the different conditions of “incongruence” between the ILE score and the qualitative HR person’s assessment. To reiterate, we employed this random assignment for the different conditions of incongruence for exploratory purposes, as also noted in the pre-registration form. In study 1, we randomly assigned participants to one of three conditions of incongruence: (a) High - the teacher with the lowest ILE score is the one with the most favorable qualitative evaluation and the teacher with the highest ILE score is the one with the most negative qualitative evaluation; (b) Medium - similar to condition a, but the teacher with the medium ILE score is the one with the most negative qualitative evaluation; (c) Modest - the teacher with the lowest ILE score has a mixed qualitative evaluation and the teacher with the highest ILE score is the one with the most favorable qualitative evaluation condition. In study 2, we omitted condition b, and randomly assigned participants to high/modest incongruence conditions. In regression Table A2, we further test the interaction between these incongruence conditions and the algorithmic v. human type of advice.
### Table A1

| Incongruence between ILE score and qualitative evaluation | Study 1 | Study 2 | Combined |
|----------------------------------------------------------|---------|---------|-----------|
| Advice n % follows advice | n % follows advice | n % follows advice |
| a. High | Algorithm 99 | 0.101 | 0.106 | 0.105 |
| | Human 94 | 0.138 | 0.084 | 0.099 |
| b. Medium | Algorithm 88 | 0.136 | - | 0.136 |
| | Human 107 | 0.131 | - | 0.131 |
| c. Modest | Algorithm 108 | 0.111 | 0.110 | 0.110 |
| | Human 109 | 0.092 | 0.107 | 0.102 |

### Regression Table A2

| Predictors | (1.1) | (1.2) | (1.3) | (1.4) | (1.5) |
|------------|-------|-------|-------|-------|-------|
| Algorithm  | 0.70  | (0.28 –1.68) | -0.80 | 0.426 | 1.30  | (0.69 –2.46) | 0.81 | 0.416 | 1.06  | (0.64 –1.77) | 0.23 | 0.822 | 0.67  | (0.31 –1.44) | -1.01 | 0.314 | 1.09  | (0.65 –1.83) | 0.34 | 0.736 |
| Medium Incongruence | 0.94 | (0.41 –2.13) | -0.15 | 0.877 | 1.36  | (0.68 –2.61) | -0.36 | 0.362 | 0.81  | (0.26 –2.15) | -0.40 | 0.691 | 1.42  | (0.71 –2.74) | 1.03 | 0.304 |
| Modest Incongruence | 0.63  | (0.26 –1.50) | -1.04 | 0.300 | 1.31  | (0.69 –2.49) | 0.83 | 0.405 | 1.03  | (0.61 –1.72) | 0.11 | 0.915 | 0.82  | (0.39 –1.72) | -0.51 | 0.607 | 1.04  | (0.62 –1.75) | 0.15 | 0.880 |
| Algorithm × Medium Incongruence | 1.50 | (0.45 –5.06) | 0.66 | 0.511 | 0.99  | (0.37 –2.62) | -0.02 | 0.983 | 2.59  | (0.60 –11.67) | 1.27 | 0.204 | 1.01  | (0.37 –2.69) | 0.02 | 0.986 |
| Algorithm × Modest Incongruence | 1.77 | (0.51 –6.26) | 0.90 | 0.370 | 0.79  | (0.33 –1.89) | -0.52 | 0.600 | 1.03  | (0.51 –2.11) | 0.09 | 0.930 | 2.04  | (0.73 –5.89) | 1.34 | 0.179 | 1.03  | (0.51 –2.12) | 0.09 | 0.926 |
| Female | | | | | | |
| | | | | | | |
| Age | | | | | | |
| | | | | | | |
| Income | | | | | | |
| | | | | | | |
| Intercept | 0.16 | (0.09 –0.28) | -6.12 | <0.001 | 0.09 | (0.06 –0.14) | -10.22 | <0.001 | 0.11 | (0.08 –0.16) | -12.02 | <0.001 | 0.10 | (0.06 –0.16) | -9.00 | <0.001 | 0.10 | (0.07 –0.15) | 12.11 | <0.001 |
| N | 605 | 904 | 1509 | 883 | 1495 |
| log-Likelihood | -217.831 | -296.789 | -515.773 | -257.427 | -507.089 |
Regression Tables A3, A4 replicate regression Tables 1 and 2 in the main paper, while adding the additional observations from study 2 ($n=316$) which we omitted from the main analyses. For this point, see footnote 9 in the main paper.

Regression Table A3

| Predictors   | Study 1 (1.1) | Study 2 (1.2) | Combined (1.3) | Combined (robust samples) (1.4) | Combined (1.5) |
|--------------|---------------|---------------|----------------|----------------------------------|----------------|
|              | OR (95% CI)   | $z$           | p-value        | OR (95% CI)                      | $z$           | OR (95% CI) | $z$ | p-value | OR (95% CI) | $z$ | p-value |
| Algorithm    | 1.02 (0.70 – 1.48) | 0.09 | 0.927 | 0.99 (0.74 – 1.34) | -0.05 | 0.960 | -1.14 | 0.252 | 1.02 (0.76 – 1.38) | 0.13 | 0.894 | 1.02 (0.70 – 1.48) | 0.09 | 0.927 |
| Female       |               |               |               | 0.74 (0.54 – 1.02) | -1.85 | 0.064 |
| Age          |               |               |               | 1.00 (0.99 – 1.01) | -0.61 | 0.540 |
| Income       |               |               |               | 1.16 (1.04 – 1.30) | 2.59 | 0.010 |
| Intercept    | 0.11 (0.08 – 0.14) | -16.01 | <0.001 | 0.12 (0.10 – 0.15) | -19.68 | <0.001 | 0.10 (0.07 – 0.14) | -15.09 | <0.001 | 0.12 (0.09 – 0.14) | -19.57 | <0.001 | 0.11 (0.08 – 0.14) | -16.01 | <0.001 |
| N            | 1220          | 1825          | 1068          | 1808                           | 1220          |
| log-Likelihood | -398.790     | -618.148      | -303.278      | -609.814                      | -398.790      |
Regression Table A4

| Predictors                              | (2.1)         | (2.2)         | (2.3)         |
|-----------------------------------------|---------------|---------------|---------------|
|                                         | OR (95% CI)   | z  | p-value | OR (95% CI)   | z  | p-value | OR (95% CI)   | z  | p-value |
| Perceived superiority of algorithms     | 17.95 (5.41 – 61.74) | 4.66 | <0.001  | 41.82 (5.41 – 361.17) | 3.49 | <0.001  | 14.15 (4.29 – 48.48) | 4.29 | <0.001  |
| Female                                  | 0.58 (0.36 – 0.91) | -2.36 | 0.018  |               |     |         |               |     |         |
| Age                                     | 1.00 (0.99 – 1.02) | 0.42 | 0.676  |               |     |         |               |     |         |
| Income                                  | 1.09 (0.92 – 1.28) | 1.01 | 0.311  |               |     |         |               |     |         |
| Intercept                               | 0.11 (0.08 – 0.13) | <0.001 |       | 0.07 (0.04 – 0.09) | -14.27 | <0.001 | 0.10 (0.08 – 0.13) | 18.75 | <0.001 |
| N                                       | 923           | 547           | 914           |
| log-Likelihood                          | -300.834      | -136.450      | -295.473      |

3. Survey

Below is the full text of the surveys (in Dutch). The texts regards both studies, unless stated otherwise. Additional comments regarding the experimental conditions are presented in square brackets. The original Qualtrics files are available upon request.

Besluitvorming door middelbareschoolbesturen in Nederland

U bent onlangs benoemd tot bestuurslid van het Talentum Lyceum. Het Talentum Lyceum is onderdeel van scholengemeenschap Stichting Hermes. Deze Scholengemeenschap beheert 23 scholen verspreid over het hele land.
Als bestuurslid bent u verantwoordelijk voor het algehele functioneren van de school, waaronder het management van personeel en middelen, de organisatie van het onderwijs en de beoordeling van de kwaliteit daarvan.

Hieronder vindt u gedetailleerde informatie over de school:

| Het Talentum Lyceum |
|---------------------|
| - Niveaus: havo, vwo (atheneum en gymnasium) |
| - Aantal scholieren: 850 |
| - Staf: 61 docenten en 13 administratief medewerkers |
| - Directeur: M. van Dijk, sinds 2015. |
| - Resultaten (2018-19): |
|   o Gemiddelde eindcijfers: 6.1 (nationaal gemiddelde: 6.4) |
|   o Slagingspercentage: 84.5% (nationaal gemiddelde: 87.5%) |
| - Jaarlijks schoolbudget (in Euros): 2.230.000 (gemiddelde schoolkosten: 255) |

Het schoolbestuur is van plan om de strategie van de school voor het komende jaar (2021) vast te stellen. Als bestuurslid wordt u gevraagd om aanbevelingen te geven over de doelstellingen van de school. Kunt u de volgende reeks doelstellingen rangschikken op volgorde van belangrijkheid (1 = meest belangrijk, 7 = minst belangrijk):

- _____ Het verhogen van de gemiddelde eindcijfers
- _____ Het verbeteren van de tevredenheid van de studenten met het onderwijs.
- _____ Het verbeteren van de tevredenheid van de studenten met het schoolklimaat en de veiligheid.
- _____ Het behoud van docenten.
- _____ Het verlagen van de operationele kosten van de school.
- _____ Anders: ____________________________________________

Nieuwe docenten worden aangenomen voor een proefperiode van een jaar. Daarna kunnen ze een vaste aanstelling krijgen, afhankelijk van de goedkeuring door het schoolbestuur. Vorig jaar zijn drie docenten aangenomen voor zo’n proefperiode, maar de school kan slechts 2 van die 3 docenten permanent in dienst nemen.
Als bestuurslid wordt u gevraagd aan te bevelen wie van de drie docenten geen vaste aanstelling zou moeten krijgen.

Om deze beslissing te vergemakkelijken is aan een medewerker van Personeelszaken van Stichting Hermes gevraagd om een korte kwalitatieve beoordeling van iedere docent op te stellen.

De beoordeling wordt daarnaast aangevuld met een externe evaluatie, uitgevoerd door Innovatieve Lerarenevaluatie (ILE)

[Human advice condition]
De ILE evaluatie wordt geleverd door consultants die diverse factoren met betrekking tot de achtergrond en het functioneren van docenten onderzoeken. Op basis hiervan maken de consultants een inschatting van hun potentieel of goed te presteren in de toekomst. De consultants komen op basis van hun vakkenkennis en ervaring in het veld tot een individuele score voor iedere docent, varierend van 1 (laagste potentieel) tot 10 (hoogste potentieel).

[Algorithmic advice condition]
De ILE evaluatie wordt voortgebracht door een zelflerend computeralgorithm (een vorm van kunstmatige intelligentie) dat diverse factoren met betrekking tot de achtergrond en het functioneren van docenten gebruikt en een inschatting maakt van hun potentieel om goed te presteren in de toekomst. Het algoritme, gebaseerd op een wiskundig model, maakt gebruik van een grote database en genereert een individuele score voor iedere docent, variërend van 1 (laagste potentieel) tot 10 (hoogste potentieel).

Overheidsorganisaties laten zich bij de uitvoering van hun taken regelmatig [bijstaan durch consultants / gebruik van zelflerende algoritmen].

[De evaluatie-methode die wordt gebruikt door ILE consultants / het zelflerende algoritme dat wordt gebruikt door ILE] is met een nauwkeurigheid van 95 procent zeer effectief gebleken bij het voorspellen van de prestaties van leraren.

Hieronder staan de profielen van de drie docenten. Elk profiel bestaat uit:

1. Een samenvatting van de beoordeling door een medewerker Personeelszaken van Stichting Hermes;
2. Een persoonlijke evaluatiescore, opgesteld door [consultants / het zelflerende algoritme] (ILE).

| Docent: * | 1. A. Verhagen ** | 2. M.S. Jansen | 3. F.E. den Heijer |
|----------|-----------------|----------------|-----------------|
|          | (Scheikunde)    | (Biologie)     | (Natuurkunde)   |

* * *
1. **Beoordeling door medewerker Personeelszaken:**

De kwaliteit van mevrouw Verhagens onderwijs is uitstekend en haar klassen hebben het zeer goed gedaan bij de centrale examens. Ze wordt ook zeer gewaardeerd door zowel de andere docenten als de studenten en de ouders. Ik geloof dat zij veel potentieel heeft als docent.

De gemiddelde scores van mevrouw Jansens klassen bij de centrale examens liggen iets onder het nationaal gemiddelde. Anderzijds is ze zeer gemotiveerd en in de loop van het jaar is ze erin geslaagd om enkele verbeteringen aan te brengen. Ik geloof dat ze potentieel heeft, maar nog veel vooruitgang moet boeken.

De scores van mevrouw Den Heijers klassen bij de centrale examens liggen ruim onder het nationaal gemiddelde. Ze lijkt niet erg gemotiveerd en in het afgelopen jaar is er weinig verbeterd in de kwaliteit van haar onderwijs. Ze voldoet niet aan de eisen die gesteld worden aan een docent op deze school.

2. **Zelflerend algoritme / consultants evaluatiescore (ILE)**

[4 / 8]***  [6 / 4]  [8 / 6]

* In study 1, the order of the three teachers was randomized.

** in the second study, we also included an additional manipulation for the teacher’s names (Dutch / Moroccan name), as explained in the main paper.

*** In study 1, we included an additional condition, where teacher 1 (Verhagen) has an ILE score of 4, teacher 2 (Jansen) has a score of 8 and teacher 3 (den Heijer) has a score of 6.

Van wie zou u aanbevelen het contract niet te vernieuwen? (Nogmaals: u wordt gevraagd 1 docent te kiezen.)

- A. Verhagen
- M.S. Jansen
- F.E. den Heijer

We vragen u nu terug te denken aan de informatie over de docent die volgens u geen vaste aanstelling zou moeten krijgen [teacher selected].

Kies de correcte zin:

De **ILE evaluatiescore** is gebaseerd op

- Een zelflerend computeralgoritme.
o Een beoordeling door consultants.
o Een beoordeling door andere docenten.

De ILE evaluatiescore van [teacher selected] was:
o Hoger (beter) dan de score van de andere twee docenten.
o Lager (slechter) dan de score van de andere twee docenten.
o Niet de laagste en niet de hoogste.

Wat was de ILE evaluatiescore van [teacher selected]?

1 2 3 4 5 6 7 8 9 10

De beoordeling door de medewerker van Personeelszaken van [teacher selected] was:
o Beter dan de beoordelingen van de andere twee docenten.
o Slechter dan de beoordelingen van de andere twee docenten.
o Niet de beste en niet de slechtste.

Hoe makkelijk of moeilijk was het voor u om tot een beslissing te komen?

Erg makkelijk                           Erg moeilijk

1 2 3 4 5 6 7

Hoe gemakkelijk of ongemakkelijk voelt u zich over uw beslissing?

Erg ongemakkelijk                     Erg gemakkelijk

1 2 3 4 5 6 7
Hoe zeker bent u van uw beslissing?

Helemaal niet  Erg
zeer zeker zeker

1  2  3  4  5  6  7

Nu willen we u vragen na te denken over de manier waarop u tot uw beslissing kwam om het contract niet te vernieuwen.

Kunt u in uw eigen woorden het *denkproces* beschrijven dat tot uw beslissing heeft geleid?

________________________________________________________________
________________________________________________________________
________________________________________________________________
________________________________________________________________
________________________________________________________________

Kunt u aangeven in hoeverre u het eens of oneens bent met de volgende stellingen, van 1 (zeer mee oneens) tot 7 (zeer mee eens):

Ik heb bij mijn beslissing veel gewicht toegekend aan *de zelflerend algoritme evaluatiescore (ILE).*

| Zeer mee | Zeer mee |
|----------|----------|
| oneens   | eens     |
| 1        | 2        | 3        | 4        | 5        | 6        | 7        |

Ik heb bij mijn beslissing veel gewicht toegekend aan *de consultants evaluatiescore (ILE).*

| Zeer mee | Zeer mee |
|----------|----------|
| oneens   | eens     |
Ik heb bij mijn beslissing veel gewicht toegekend aan de beoordeling door de medewerker van Personeelszaken.

| Zeer mee | Zeer mee |
|----------|----------|
| oneens  | eens     |

1 2 3 4 5 6 7

Heeft u nog andere aspecten in uw overweging meegenomen? Kunt u aangeven welke?

________________________________________________________________
________________________________________________________________
________________________________________________________________
________________________________________________________________
________________________________________________________________
________________________________________________________________

Welke van de volgende zinnen beschrijft het beste hoe u tot uw beslissing bent gekomen?

- Ik heb de docenten eerst gerangschikt op basis van de ILE evaluatiescore. Daarna heb ik mijn rangschikking bijgesteld (naar boven of naar beneden) in het licht van de beoordeling door de medewerker van Personeelszaken.

- Ik heb de docenten eerst gerangschikt op basis van de beoordeling door de medewerker van Personeelszaken. Daarna heb ik mijn rangschikking bijgesteld (naar boven of naar beneden) in het licht van de ILE evaluatiescore.

- Anders: ____________________________________________________
Om er zeker van te zijn dat u de vraag zorgvuldig hebt gelezen vragen we u het getal 99 onder “Anders” te typen.

1. Zeer weinig
2.
3.
4.
5.
6.
7. Zeer veel
Anders: ________________________________________________

[The following questions appeared only for participants assigned to algorithmic advice condition]
Kunt u aangeven in hoeverre u het eens of oneens bent met de volgende stellingen, van 1 (zeer mee oneens) tot 7 (zeer mee eens):

Computeralgoritmen houden met meer informatie rekening dan mensen.

| Zeer mee | Zeer mee |
|---------|---------|
| oneens | eens |

| 1 | 2 | 3 | 4 | 5 | 6 | 7 |

Computeralgoritmen komen tot betere beoordelingen dan mensen bij de meeste taken.

| Zeer mee | Zeer mee |
|---------|---------|
| oneens | eens |

| 1 | 2 | 3 | 4 | 5 | 6 | 7 |

Bij de beoordeling van andere mensen komen computeralgoritmen tot eerlijkere oordelen dan mensen.

| Zeer mee | Zeer mee |
|---------|---------|
| oneens | eens |

| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
We willen u nu enkele algemene vragen stellen over uw opvattingen over het gebruik van computeralgoritmen door overheidsorganisaties.

In de afgelopen jaren hebben overheden zelflerende algoritmen gebruikt bij het nemen van besluiten op een aantal beleidsterreinen, zoals de gezondheidszorg, het onderwijs en het veiligheidsdomein (bijv. bij de politie).

Geef aan in hoeverre u het eens bent met de volgende zinnen:

Het gebruik van algoritmen door overheidsorganisaties kan de kwaliteit van hun beslissingen verbeteren.

| Zeer mee | Zeer mee |
|----------|----------|
| oneens  | eens     |

Het gebruik van algoritmen door overheidsorganisaties kan leiden tot eerlijkere beslissingen.

| Zeer mee | Zeer mee |
|----------|----------|
| oneens  | eens     |

Beslissingen door overheidsorganisaties gebaseerd op algoritmen kunnen worden vertrouwd.

| Zeer mee | Zeer mee |
|----------|----------|
| oneens  | eens     |

Overheidsbeslissingen gebaseerd op algoritmen kunnen oneerlijk zijn, omdat:

______________________________
Was u al bekend met het gebruik van algoritmen door overheidsorganisaties voordat u aan deze enquete begon?
- Nee
- Ja

Kunt u een voorbeeld geven?

________________
________________________________________________
________________

Tot slot willen we u nog enkele algemene vragen stellen over uzelf:

Wat is uw leeftijd?

Heeft u schoolgaande kinderen?
- Nee
- Ja - op de basisschool
- Ja - op de middelbare school

Wat is uw hoogst genoten opleiding?
- VMBO/Mavo
- Havo
Volgens het Centraal Planbureau (CPB) ligt in 2019 het gemiddelde bruto inkomen (in Euros) voor personen werkzaam in Nederland op 35.500 per jaar ofwel 2.739 bruto per maand. Ligt uw inkomen:

- Ver onder het gemiddelde
- Iets onder het gemiddelde
- Rond het gemiddelde
- Iets boven het gemiddelde
- Ver boven het gemiddelde

In welke provincie woont u?
________________________________________

Werkt u (of heeft u gewerkt) in het onderwijsveld?

- Nee
- Ja

In welke functie?
________________________________________
________________________________________
________________________________________
________________________________________
________________________________________
Is er iets wat u graag met ons wilt delen?

________________________________________________________________
________________________________________________________________
________________________________________________________________
________________________________________________________________

We danken u hartelijk voor uw deelname aan dit onderzoek.

Mocht u vragen hebben of een samenvatting van de bevindingen van het onderzoek willen ontvangen, dan kunt u ons benaderen via onderstaande e-mailadressen.

Met vriendelijke groet,
[AUTHORS’ UNIVERSITY DEPARTMENT]