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**Proceedings of the Weizenbaum Conference 2023:
AI, Big Data, Social Media, and People on the Move**

THE PROBLEMS OF THE AUTOMATION BIAS IN THE PUBLIC SECTOR

A LEGAL PERSPECTIVE

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ABSTRACT

The automation bias describes the phenomenon, proven in behavioural psychology, that people place excessive trust in the decision suggestions of machines. The law currently sees a dichotomy—and covers only fully automated decisions, and not those involving human decision makers at any stage of the process. However, the widespread use of such systems, for example to inform decisions in education or benefits administration, creates a leverage effect and increases the number of people affected. Particularly in environments where people routinely have to make a large number of similar decisions, the risk of automation bias increases. As an example, automated decisions providing suggestions for job placements illustrate the particular challenges of decision support systems in the public sector. So far, the risks have not been sufficiently addressed in legislation, as the analysis of the GDPR and the draft Artificial Intelligence Act show. I argue for the need for regulation and present initial approaches.

1 INTRODUCTION

Digital transformation has led to the ubiquity of algorithmic decision-making. Public and private actors are replacing previously purely human decision-making processes with processes that integrate computer systems or pre-structuring human decisions with automated decision suggestions. In the administrative sector in particular, this increasing use gives rise to numerous legal issues.¹ So-called Algorithmic-Decision-Making-Systems (ADM) make existentially important decisions that affect people's lives, such as the distribution of child benefits,² the allocation of university places³ or support measures in employment services.⁴ There are countless articles about the benefits and risks of fully automated decisions. Societal risks,⁵ potential for discrimination,⁶ ethical questions,⁷ legal redress deficit⁸ and constitutional requirements such as legitimisation⁹ and transparency¹⁰ are the subject of an ongoing debate. The general aim of using technology and automation in public administration is to make decision-making processes more effective, efficient, rational, or neutral. The factual basis as a formerly analogue reality of life has been datafied and thus supposedly rendering it calculable. But numerous examples of algorithmic errors¹¹ due to inadequate databases, programming errors, or incorrect application have shown that the digitalisation of decision-making processes is neither efficient, desirable, nor compatible with the principles of the rule of law¹² and the protection of fundamental rights in all areas.¹³

In this context, the supposedly clear dichotomy between human and machine decision-making processes suggests a clear distribution of risks to the detriment of full automation,¹⁴ whereas human decisions seem to be sufficiently constrained by existing normative structures such as justification requirements, bias rules, time periods, etc. to legitimise the content of the decision. The risks of these hybrid decision-making processes are not covered by the regulatory systems, for example, there are no provisions for decision-support systems in German administrative law, only a reference to fully automated administrative acts. I focus here on the case of decision-support systems in the administrative sector which produce automated proposals for human decision-makers.

¹ (Ruscheimer 2023 i.E.).

² https://www.autoriteitpersoonsgegevens.nl/sites/default/files/atoms/files/onderzoek_belastingdienst_kinderopvangtoeslag.pdf.

³ (Martini et al. 2020).

⁴ (Allhutter et al. 2020), (Scott et al. 2022).

⁵ Eg. (Pasquale 2015).

⁶ Eg. (Wachter 2019).

⁷ Eg. (Mühlhoff 2020).

⁸ (Martini, Ruschemeier, and Hain 2021).

⁹ Eg. (Liu, Lin, and Y.-J. Chen 2019).

¹⁰ Eg. (Burrell 2016).

¹¹ (O'Neil 2017).

¹² (Kolain and Ruschemeier 2023).

¹³ (Nink 2021).

¹⁴ See the specific norms for algorithmic administrative acts in German Administration Law: § 35a Administrative Procedures Act, § 88 (4) Tax Code; § 31a Social Code X. (Kahneman et al. 2016) argue the opposite, namely that algorithms make better decisions than humans.

Human decisions follow a limited rationality.¹⁵ In an increasingly complex world, it seems more and more difficult to consider all the relevant factors when making decisions.¹⁶ The use of algorithm-based systems to alleviate human decision-making processes is therefore ubiquitous. However, the focus of (scientific) discussions is mainly on visions of “artificial intelligence”, robotics, and fully automated decision-making processes. Thus, the risks of algorithmic decision support are not sufficiently reflected in legal and institutional terms, but are in fact widespread.¹⁷

In between these two poles of fully automated and fully human decision-making lies the as-yet unestablished (legal) category of decision-support, which also seems ubiquitous in everyday life. Digital devices, platforms, or other network-based services are constantly suggesting decisions: from operating modalities and default settings to recommendation algorithms for advertising and content. These decision-support systems become problematic when they are subject to different parameters than purely human or fully automated decisions, parameters which are previously unknown and lead to anomalies, such as the automation bias.¹⁸

Automation bias is the phenomenon, well established in behavioural psychology, in which people trust the suggestions and decisions of machines against their better judgement.¹⁹ With the widespread use of such systems, for example in education or benefits administration, such biases develop a leverage effect and multiply the number of people affected. Especially in environments where people have to make a large number of similar decisions on a routine basis, the risk of automation bias increases, and expert knowledge alone is not a sufficient defence. At present, the problem of automation bias is not addressed by legislation. External factors such as time pressure or the effort required to check the algorithm can encourage such behaviour.²⁰

I will show the legal difficulties inherent in automation bias using the case study of the ASM algorithm (2) and then look at the current legal situation (3) before considering the need for regulation (4).

2 CASE STUDY: THE AUSTRIAN AMS-ALGORITHM AND SIMILAR SYSTEMS

The Austrian ASM-algorithm²¹ has been used in the placement of unemployed people and was designed to help case workers make more efficient use of resources in the long term.²² For this purpose,

¹⁵ (Kahneman 2011).

¹⁶ (Ruscheimer 2022).

¹⁷ (Wachter, Mittelstadt, and Russell 2021).

¹⁸ Some studies (Alon-Barkat and Busuioc 2023) also find other human biases beyond overreliance on machine output, such as selective adherence, i.e. adherence to machine output that systematically differs across sensitive demographic dimensions of decision subjects.

¹⁹ Recently in the context of judicial reviews: (Kazim and Tomlinson 2023). Regarding public administration: (Alon-Barkat and Busuioc 2023); (Green and Y. Chen 2019). See also: (Bailey and Scerbo 2007); (Lyell and Coiera 2017b); (Parasuraman, Molloy, and Singh 1993); (Indramani L. Singh, Anju L. Singh, and Proshanto K. Saha 2007); (Rovira, McGarry, and Parasuraman 2007); (Snow 2021).

²⁰ (Lyell and Coiera 2017a); (Pilniok 2022).

²¹ Arbeitsmarktchancen-Assistenz-System des Arbeitsmarktservices (AMS) Österreich; <https://iab.de/iab-veranstaltungen/einblicke-in-das-arbeitsmarktchancen-assistenz-system-der-sogenannte-ams-algorithmus-des-arbeitsmarktservice-ams-oesterreich/>.

²² Currently, the application is suspended due to an ongoing court case. (Der Standard 2022).

the programme divided jobseekers into three groups according to their calculated chances on the labour market: high, medium and low. The AMS-model considered personal characteristics such as age, gender, education, health limitations, caring responsibilities, education, and citizenship.²³ On the basis of the published model, it can now be seen that the model deducts certain points for being a woman (0.14 points) as well as for potentially having care responsibilities as a woman (0.15 points). This reveals that the existence of care responsibilities alone played a role in a woman's future job chances. All people over 30 are also penalised on the basis of their age alone, and the penalty is even more drastic from the age of 50 (0.7 points). People with 'health problems' are also penalised by the system (0.67 points), as are people from non-EU countries.

In addition to the obvious potential for discrimination, other legal problems arose: the competent data protection authority (DPA) prohibited the further use of the programme, as it constituted illegal profiling and a violation of Art. 22 of the GDPR which prohibits fully automated individual decisions with legal effect or similar impairments.²⁴ The DPA argued that while the final decision rested with the person responsible according to internal PES guidelines, these internal instructions have no "external effect" and are therefore not binding on the authority concerned. In this respect, the affected persons cannot refer to them in a legally effective manner and thus cannot demand a review. The fact that in some cases the counselling time allocated was only ten minutes speaks in favour of a routine acceptance. Furthermore, the DPA argued that it could be assumed that counsellors would increasingly rely²⁵ on the decision of the AMS as a result of COVID-19. As genuine supervision by a human being is therefore "not bindingly ordered (in the sense of a legal guarantee) for all individual cases and thus not fully guaranteed", Article 22 of the GDPR should be applied with reference to the guidelines of the Article 29 Working Party,²⁶ which assumes an "automated decision" in the sense of Article 22 GDPR in cases in which automatically calculated results are routinely simply adopted.

In the ensuing legal dispute, however, the Austrian Federal Administrative Court proceeded on the basis of a purely formal assessment of the decision-making structure and did not address the risks of automation bias. The court argued that the assessment was only carried out by the relevant consultants using the model and that routine adoption did not carry any great significance. An appeal against the decision has been submitted, but no decision has been made so far, and the AMS-model is not in use.²⁷ A similar system has been used in Poland, where statistical analysis has also shown that case-workers made changes to the automated classification of jobseekers in only 0.58% of the cases examined.²⁸

Since, according to the court, this was not a fully automated decision within the meaning of Art. 22 GDPR, despite the many indications suggesting the case handlers simply relied on the suggestions of the system, the protective mechanisms of Art. 22 GDPR do not apply either. In the court's opinion, the decisions were thus purely human decisions; the factual binding effect of the machine suggestions in combination with the internal guidelines was not considered. Thus, constellations of potential automation bias fall between the cracks: the actions of data subjects are made considerably more

²³ https://ams-forschungsnetzwerk.at/downloadpub/arbeitsmarktchancen_methode_%20dokumentation.pdf

²⁴ Österreichische Datenschutzbehörde, decision 16.8.2020, D213.1020, 2020.0513.605.

²⁵ (Allhutter et al. 2020) point out, that the system's output is supposed to be a "second opinion" but will become a "first opinion" in practical use due to the short time available to case handlers. See also (Scott et al. 2022).

²⁶ (Art. 29 Data Protection Working Group 2017).

²⁷ (Scott et al. 2022).

²⁸ (Niklas, Sztandar-Sztanderska, and Szymielewicz 2015), S. 28, (Scott et al. 2022).

difficult by the engagement of non-transparent systems within the decision-making process, but they are also not entitled to the protection of the additional rights which are only triggered by fully automated decisions.

So far, regulators and courts have ruled that a formal human-in-the-loop is sufficient to prevent a fully automated decision. This means that the problem of automation bias cannot be solved by merely banning fully automated decisions. This could indicate that a new kind of decision category is needed to address human-machine interactions that produce decision-relevant output.

3 DECISION SUPPORT SYSTEMS IN LAW

As the cases show, data protection law does not adequately address the problem of automation bias. In general, the law has so far distinguished between two forms of automated decision systems (ADM) fully automated ADM and partially automated ADM, i.e. decision-support systems with a human in the loop.²⁹

3.1 Automation Bias and the GDPR

This interface between machine suggestions and human final decisions has so far only been dealt with in passing, especially in the context of data protection law.³⁰ Article 22 GDPR establishes the right not to be subject to a decision based solely on automated processing, including profiling, which produces legal effects or significantly affects that individual (the data subject). The prerequisite for its application is the processing of personal data within the scope of the GDPR, which also applies to public authorities. The right under Art. 22 (1) GDPR, which is interpreted as a prohibition, does not apply if the decision is necessary for the performance of a contract (Art. 22 (2) a)), if a legal basis has been created that provides sufficient safeguards for the rights, freedoms and interests of the data subject (Art. 22 (2) b)), or if it is based on an explicit consent (Art. 22 (2) c)). None of these exceptions apply to public employment services.

It is therefore crucial to understand a decision based solely on fully automated processing. The exact interpretation is unclear and disputed.³¹ Legally, there can be no decision if the person concerned already lacks the capacity to decide. In a purely human-based process, this would be the preparation stage for a decision, for example, with the scanning of documents.

Thus, in the example of the Austrian court, if a human retains substantive decision-making power, it could be argued the machine is merely preparing the information, and there is no fully automated decision from a purely external point of view.

However, substantive decision-making power is not congruent with a decision if it is not exercised. It is only when the decision-making power is exercised by a human being that it has an effect on the result. In my opinion, it is not sufficient to limit oneself to a plausibility check or not to influence the automated process. These difficulties of interpretation are compounded by problems of verifiability; decision-making is an internal process that can at best be presumed on the basis of external evidence.

²⁹ (Pilniok 2022).

³⁰ (Martini 2021); (Martini, Ruschemeier, and Hain 2021), (Steinbach 2021).

³¹ (Bygrave 2020).

If the agents follow the suggestion, it is difficult to actually prove whether a decision has been consciously made or whether a suggestion has been passively adopted.

The formal understanding of fully automated decision-making systems in Art. 22 GDPR provides a normative incentive to develop decision support systems that are not subject to the requirements of the GDPR. However, decades of experience from various application areas,³² e.g. aviation safety, medicine, etc., as well as basic psychological research³³ shows that simply assuming a human-in-the-loop approach is by no means a sufficient protection. The law should recognise the psychological and technical factors in play in such decision support systems, and develop legal solutions to minimise the corresponding risks. Standards such as Art. 22 GDPR should be read more as a socio-technical norm,³⁴ or such norms should be created. Many legal requirements do not reflect the fact that digitalisation is a socio-technical development that only works in the interplay between human action and technology.³⁵ Digitalisation only exists as a result of human-driven processes, but it is increasingly influencing how those processes play out.

3.2 The forthcoming Artificial Intelligence Act and the automation bias

The draft on the Regulation of Artificial Intelligence³⁶ (AI-Act) at Union level implements the requirement for human oversight in decisions involving artificial intelligence in Art. 14 (2). High-risk AI systems should therefore “be designed and developed so that they can be effectively supervised by natural persons for the duration of the use of the AI system”. Article 14 (3) provides that human oversight should either be built into the system (lit. a) or the need for human oversight be highlighted to the user (lit. b) to allow users to understand and be aware of the capacities of the system, and subsequently to interpret, decide on, or deviate from the suggested information. In particular, users are aware of “the danger of potentially over-relying on the output of a high-risk AI system (automation bias) in particular for high risk AI systems used to provide information or recommendations to be taken by natural persons.” Through “human supervision”, users should, depending on the circumstances and within a proportionate framework, be able to monitor the AI system (para. 4 lit. a) or, in individual cases, to decide against the output of the AI software (para. 4 lit. d), i.e. to follow or not follow the decision proposal generated by the AI. Article 14 (4) (b) explicitly mentions the automation bias. The measures referred to in paragraph 3 are intended to enable the individuals to whom human oversight is assigned to remain *aware* of the possible tendency to automatically rely or over-rely on the output produced by a high-risk AI system (‘automation bias’), in particular for high-risk AI systems used to provide information or recommendations for decisions to be taken by natural persons. The actual business conditions for using AI software will usually be such that although users are ‘aware’ of the biases of the automation, they will not take active control over the decision-making process. For this, the institutional framework conditions of the decision-making situation must be changed to provide time and incentives for administrators to use their own decision-making power, and scope for deviation from system proposals.

³² (Parasuraman and Riley 1997).

³³ (Lyell and Coiera 2017a).

³⁴ (Djeffal 2021).

³⁵ (Mühlhoff 2020).

³⁶ Proposal for a Regulation of the European Parliament and of the Council Laying down harmonized rules on Artificial Intelligence (Artificial Intelligence Act) and amending certain union legislative acts. COM/2021/206 final.

It is welcome that the proposed regulation recognises the problem of automation bias. However, its scope is limited to the specific high-risk systems listed in Article 6 in conjunction with Annex III, the scope of which is still evolving during the legislative process. Currently, access to and usage of essential private services, public services, and benefits are envisaged as high-risk systems.³⁷ Moreover, thus far Art. 14 AI-Act only refers to technical measures; organisational requirements, which in particular consider the context of the decision, are *prima facie* not required.

4 A NEED FOR NEW REGULATION?

Automation bias remains inadequately addressed by the current legal instruments. Protective mechanisms are needed, particularly in the area of administrative decisions governing existential issues such as employment services and benefits. Interdisciplinary findings from technical science and psychology should be included in the process, with a distinction made between substantive legal limits and procedural requirements.

In administrative law, automation bias can constitute a violation of the principle of official investigation or a failure of discretion. So far, these consequences have not been reflected normatively. Further challenges arise in the context of provability in judicial proceedings; without insight into the internal decision-making process those affected face greater difficulty in proving automation bias. As explained elsewhere, in these cases, evidence can be facilitated.³⁸ This is justified by a distribution of risk as an extension of the rule of law principle: for the state to reap the fruits of the efficiency from using the system, it should then also have to bear the risk and be able to prove that there is no automation bias risk, e.g. through deviation rates or sufficient processing time.

In certain areas sensitive to fundamental rights, such as criminal law, but also in the case of vital administrative services of general interest, systems should not make detailed proposals for decisions, but should be used only as a tool for establishing the facts. In other areas, procedural mechanisms should be put in place to mitigate the risk of automation bias, such as confirmation requirements, justification requirements by the human decision-maker, or a four-eye principle. Insights from psychology, computer sciences, and administrative sciences should be used to determine what kind of confirmation mechanisms are useful, how user interfaces can be constructed, and which technical and institutional safeguards can be considered. Procedurally, time pressure in mass procedures should be considered as risk factor for automation bias, especially if a very short decision time is accompanied by a predominant acceptance of the system proposal.

In decision-making contexts that are particularly sensitive in terms of fundamental rights, it may be appropriate to impose a burden of proof on a case officer who makes extensive use of decision support systems in order to ensure that they address the content of the proposed decision. In any case, it should not be more time-consuming to deviate from the algorithm-based recommendation than to follow the proposed decision.

³⁷ Annex III (5): Access to and enjoyment of essential private services and public services and benefits: (a) AI systems intended to be used by public authorities or on behalf of public authorities to evaluate the eligibility of natural persons for public assistance benefits and services, as well as to grant, reduce, revoke, or reclaim such benefits and services

³⁸ (Martini, Ruschemeier, and Hain 2021); (Ruscheimer 2023).

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