Algorithms in the Workplace, an Unbiased Technology?[1]

Lidia de la IGLESIA AZA[2]

Abstract

This study analyses how biases may emerge in algorithms due to human intervention and explores the legal risks associated with these biases, conceptualising algorithm as a sufficiently detailed and systematic instruction of action to solve a mathematical problem so that, when implemented correctly, the computer computes the correct output for each correct set of inputs.

The findings highlight several specific risks of algorithmic bias without explicit intent. Additionally, the limited case law reviewed indicates a growing but still underdeveloped judicial recognition of these risks. The results underscore a need for legal frameworks to more explicitly address algorithmic transparency and accountability, especially where human biases may disproportionately affect certain demographic groups or individual rights.

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JEL Classification: K3, J7

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1. Introduction

Algorithms have been gradually replacing purely human systems of data control and classification, but algorithms require for their operation a code aimed to formalize a problem in mathematical terms. Therefore, the algorithm is fed by the decisions of the people who program it, since it must be able to select the solution to the problem posed among all the possible or existing correlations, so the predictive model on which it rests is based on the prior indication of the programmer (Zuiderveen Borgesius, F. 2018, p. 16).

As said (Krafft, 2022), an algorithm is a sufficiently detailed and systematic instruction of action to solve a mathematical problem so that, when implemented correctly, the computer computes the correct output for each correct set of inputs.

Based on this scheme of operation, algorithms can be designed to offer different services, many of them in the field of labour relations, which has led to the emergence of new forms of candidate selection in recruitment, evaluation of skills or performance of workers, career advancement, determination of working hours or

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[2] University of Santiago de Compostela, Spain. Lidiadelaiglesia.aza@usc.es

wages, monitoring in the workplace, termination of employment contract and others (Álvarez Cuesta, 2020).

These managerial powers that some companies have delegated to algorithmic systems are intended to rely on the objectivity, reliability, impartiality or neutrality of decisions. Thus, in principle, algorithms are devoid of people's biases, impressions, or prejudices (Bertail, 2019, p. 6).

While the phenomenon of algorithmic-based business decision making is spreading, one of the first testing grounds has been digital work platforms. In the on-demand economy, all production, organizational and labour systems are based on algorithms, embedded in applications or software. The basic function of these programs is the connection between supply and demand and the organization of productive forces and workers within the "digital" framework of the company (Gil Otero, 2022, p. 67). The companies that own the digital platforms pursue consumer satisfaction as the goal, and to achieve this, they design their algorithm to allow them to assign the clientele's requirements to the best rated professionals.

2. Which is the issue with algorithms?

Algorithmic decision-making is increasingly prevalent in human resource management serving as a valuable source of information and guidance. Defined as the automation and standardization of routine workplace decisions, algorithmic decision-making entails automated choices and remote oversight that were traditionally handled by humans (Möhlmann, 2017). This shift to algorithms for decision-making brings notable implications for individuals and society, influencing how organizations optimize their processes (Chalfin, 2016; Lee, 2018; Lindebaum, 2018). With algorithms, organizations can more efficiently identify hidden talent and screen large volumes of job applications, enhancing both efficiency and accuracy in Human Resources operations (Silverman, 2018; Carey, 2016; Savage, 2016).

The primary drivers behind algorithmic decision-making include reducing costs and saving time, minimizing risks, enhancing productivity, and improving the reliability of decisions (Suen, 2019; MacColl, 2019; McDonald, 2019; Woods, 2020). Beyond these economic motivations, companies aim to reduce human biases—such as prejudices and subjective beliefs—by implementing algorithmic approaches, increasing objectivity, consistency, and fairness in Human Resources processes. (Langer, 2019; Raghavan, 2020).

However, relying solely on algorithmic decision-making carries potential risks of discrimination and unfairness (Simbeck, 2019). Algorithms can produce biased outcomes if they rely on inaccurate (Kim, 2019, p. 817), biased (Barocas, 2016, p. 671), or unrepresentative data (Suresh, 2019). As a result, biased training data may lead algorithms to reinforce or replicate existing biases in their decisions (Chander, 2016, p. 1023).

But accessing the algorithm data to assess the existence of bias is complicated. How to overcome the lack of transparency in the nature and effects of algorithms? How can victims and lawyers establish evidence of discrimination considering algorithms' technological and technical complexity? While the CJEU indicated in Meister[3] that a private employer is not required to disclose information regarding the recruitment process, it also established in a consistent line of case law that transparency is a precondition for the effective enforcement of the non-discrimination principle.

So, in these basis, basic transparency, openness and disclosure requirements need to apply to algorithmic models to enable identification of discriminatory practices and effects and to allow applicants to make prima facie cases of discrimination (Palmer, 2019; Castets-Renard, 2018).

It can be stated that our legal framework can pursue discrimination when it occurs. The breadth with which anti-discrimination regulations are interpreted allows discriminatory algorithmic schemes to fit within them, giving special prominence to indirect discrimination, but a proper legal defence must start with the definition, delimitation, and understanding of algorithmic frameworks. Knowing whether algorithmic discrimination stems from the target variable, customer evaluations, or the idiosyncrasies of machine learning is essential to determine the exact origin of that discriminatory decision and consequently, the type and cause of discrimination.

The use of algorithms should be a good ground to minorities, women and other population sectors to engage in labour market, but just if the algorithm is fed with neutral data inputs.

This is one of the aims of the Regulation (EU) 2024/1689 of the European Parliament and the Council of 13 June 2024 laying down harmonised rules on artificial intelligence and amending Regulations (EC) No 300/2008, (EU) No 167/2013, (EU) No 168/2013, (EU) 2018/858, (EU) 2018/1139 and (EU) 2019/2144 and Directives 2014/90/EU, (EU) 2016/797 and (EU) 2020/1828 (Artificial Intelligence Act): "to promote the uptake of human centric and trustworthy artificial intelligence (AI) while ensuring a high level of protection of health, safety, fundamental rights as enshrined in the Charter of Fundamental Rights of the European Union (the 'Charter'), including democracy, the rule of law and environmental protection, to protect against the harmful effects of AI systems in the Union, and to support innovation".

As is said in this Regulation, "AI systems used in employment, workers management and access to self-employment, in particular for the recruitment and selection of persons, for making decisions affecting terms of the work-related relationship, promotion and termination of work-related contractual relationships, for allocating tasks on the basis of individual behaviour, personal traits or characteristics and for monitoring or evaluation of persons in work-related contractual relationships, should also be classified as high-risk, since those systems may have an appreciable impact on future career prospects, livelihoods of those persons and workers' rights. (…) Throughout the recruitment process and in the evaluation, promotion, or retention of persons in work-related contractual

[3] Judgment of the Court of 19 April 2012. ECLI:EU:C:2012:217

relationships, such systems may perpetuate historical patterns of discrimination, for example against women, certain age groups, persons with disabilities, or persons of certain racial or ethnic origins or sexual orientation".

So, as set out in the Annex III, regarding article 6, employment, workers' management and access to self-employment is consider a High-risk AI issue, what means that a risk management system shall be established, implemented, documented and maintained. (article 9). The intention of this Regulation is to minimise the risks admitted by the regulation itself as existing: that is, profiling systems and biases in the configuration of the AI systems itself.

It will take time since this implementation to validate the success of this regulation, but, at least, is a beginning in the conception that IA must be limited and regulated in the field of employment.

3. Platform works

Originally perceived as mere novelties, labour platforms have emerged as significant entities within both domestic and global labour markets. From the standpoint of labour and the future of work, platforms should be regarded as a novel economic entity, separate and distinct from traditional markets, firms, and networks (Vallas, 2020).

This kind of work has been labelled as the gig economy and consists both of work that is transacted via platforms but delivered locally and thus requires the worker to be physically present, and work that is transacted and delivered remotely via platforms (Wood, 2019).

These platforms work through algorithmic frameworks that have clear implications for the labour declaration of platform workers (Gil Otero, 2020). Various approaches to this phenomenon are revealing that algorithms can constitute a source of labour discrimination within the platform economy. In this regard, the existence of a gender pay gap in the Uber platform has already been revealed, with the pay of female drivers being 7% lower than that of male drivers (Cook, 2021), and the Court of Bologna has already declared that Deliveroo's internal algorithm is discriminatory[4].

The efficiency of work on digital platforms rests on a matching algorithm, which assigns client services to workers, but that matching has its basis in a ranking algorithm underpinned by profiling.

In this way, the performance evaluations of the workers are carried out, giving rise to scores from which a ranking of workers is derived, according to which the worker best scored by the classification algorithm will receive more and higher quality services from the matching algorithm. Thus, the joint operation of algorithms determines the job opportunities and the overall compensation to be received by each worker. The intention of this system based on the algorithms is to organize the

[4] Bologna Ordinary Court of 31 December 2020, rec. 2949/2019

productive task in the most incentive way to improve the service possible (Countouris, 2018, p. 488).

But the design of the ranking algorithm can lead to biased scores of workers, and, considering that such biased scores are directly related to job access possibilities, it can lead to discriminatory employment decisions.

Structural discrimination, which is the product of past discrimination institutionalised over time, is mirrored in data, and by it, in algorithms. For instance, if an algorithm is trained using a dataset gathering all employees hired in the past to predict which employees should be hired in the future based on their potential performance, it might reproduce discrimination against women and overwhelmingly correlate the male gender to expected job performance (Caliskan, 2017; Bolukbasi, 2016). This is because past hiring decisions are infected with discriminatory gender stereotypes that will be reproduced by the algorithm (Lu, 2018, p. 3). So, historically rooted gender divisions of labour are replicated, and may be amplified, in the digital economy, and particularly in platform-mediated work.

Gig economy jobs divide work into small pieces and then offer those pieces of work to independent workers in real-time, allowing for easy substitution of work across workers. This ease of worker substitutability should severely limit a "job-flexibility penalty," and potentially exhibit little to no gender pay disparity as it´s known (Blaud, 2017) that one of the page gaps between women and men is caused by the limited disponibility of women caused by the care duties. Based in this premises, as more industries gravitate towards using gig work, the importance of the job-flexibility penalty in gender wage inequality should weaken.

4. Discrimination in the platform work.

The studies in this issue (Cook, 2021) shows that the historical discrimination that women have suffered in the workplace is also evident in this area. Thus, just as an example, in the field of platform drivers, e.g. UBER, the fact that male drivers are willing to work in environments (bar areas) and at times (night shifts) when violence is more likely to occur, penalises female drivers. In no case can the fact of giving up these more lucrative shifts be separated from factors such as reduced physical strength and care work. It is therefore not an option based on voluntary choice but based on acquired safety knowledge and socially imposed care obligations. These facts are a biased estimate of the job-flexibility penalty.

It is not that women do not want to access better paid shifts; it is that there are a series of reasons that prevent this group from accessing these services. In this way the gendered organisation of society might weight negatively in algorithmic scoring, infringing on the principle of equal pay and thus indirectly discriminating against women.

In gig economy as the possible biased scores of digital platform workers stem from the processing of the data by the ranking algorithm, the limitation in the election of the shifts penalise women.

The score of these workers depends on two main types of algorithmic rankings. On the one hand, there is the ranking based on internal data, i.e. data that reflects the history of each worker in the platform. This is data is available to the platform, thanks to its own monitoring and surveillance mechanisms. On the other hand, there is the classification made under the cover of external data, i.e. data that a third party other than the worker enters the platform. The difference between the two types of data is fundamental, insofar as their processing can give rise to different examples of discrimination and, therefore, to different responses from anti-discrimination regulations.

Taking about internal data, a good example of platform work is Deliveroo. which is dedicated to the home delivery of prepared food. This platform has a system for organising work by weekly time slots. On a specific day of each week, the available time slots for the following week are made available to workers. In principle, the idea is that employees can book and select the working hours that suit them best from this template. However, access to this template is not done simultaneously by all workers, but in a staggered manner. Deliveroo's system privileges access to the work pool according to a reputational ranking, organised by points. In this way, the workers with the highest scores according to the ranking access the platform at 11:00 a.m., while the remaining workers access the platform at the following shifts, at 1:00 p.m. and 3:00 p.m.

To determine each worker's score, Deliveroo's ranking algorithm uses the criteria or indicators of ‘reliability’ and ‘rider participation’. On the one hand, the reliability indicator measures the number of times the rider does not participate in the work session even though he/she booked it the previous week. On the other hand, the rider participation index measures the number of times the rider has been available to deliver at times of peak demand, especially from Friday evening to Sunday afternoon. This internal data, which is evaluated by the ranking algorithm, means that, in principle, the worker is ranked for strictly objective reasons linked to the work he/she has been doing on the platform. However, it should not be overlooked that these indications are essentially based on the worker's availability. This entails a considerable risk, since behind the degree of availability of each worker there may always be reasons relating to his personal and/or family life that are not foreseen by the algorithm when it is carrying out its classification (Gil Otero, 2020).

It is precisely this risk that has given rise to the first judgment in Europe concerning algorithmic discrimination at work on digital platforms, as mentioned above. The Ordinary Court of Bologna, in its ruling of 31 December 2020 (rec. 2949/2019), considered that the sorting algorithm based on Deliveroo's internal data - commonly known as ‘Frank’ - violated the right to non-discrimination of workers. This ruling assessed the lawsuit brought by a group of Italian trade unions, who believed that Deliveroo's system placed workers who supported a strike in a situation of inequality. And this is because the fact that a worker was on strike and was not available not only implied the loss of that time wages. In turn, as if it were a chain, this absence would cause their algorithmic participation rate to fall their score in the ranking and, consequently, their chances of accessing work as a priority in the following weeks. All this, despite exercising a constitutionally protected fundamental right.

But the court's reasoning can be extrapolated perfectly well to the situation of rest after childbirth, risk during pregnancy or childbirth, that is, to situations specifically protected by law.

In the Bolonia's Court view, by using this ranking algorithm the company was discriminating against workers, as it deliberately ignored the reasons for the rider's absence or unavailability. The algorithmic should have a mechanism to neutralise a negative score when it was based on a ground specially protected by the right to equality (Fernández Sánchez, 2021, p. 189).

As it´s well known, "formal equity" is insufficient to achieve true equality. That´s why Scholars (Sheppard, 2017) advocate for the concept of "substantive equality" to effectively combat inequality by acknowledging the deeply ingrained social and systemic dimensions of discrimination.

So, the fact that algorithms do not consider the circumstances of the worker may therefore result in discrimination against the worker, when no appreciating specially protected characteristics lead to a disadvantageous result. The criteria linked to the performance of the job, can´t be apart from the characteristics specially protected by anti-discrimination regulations (Xenidis, 2020, p. 12).

The lack of availability of a female worker may also be structural, due to the group's own situation in the labour market. Just-in-time working systems disadvantage women workers, who adopt work-life balance measures to a greater extent than men. The conception of the 'best worker' as the one with the highest rate of availability can lead, for example, to women workers who are subject to reduced working hours being ranked lower in terms of reputation than men workers. Comparing their performance with that of 'full-time' workers would attribute to them lower skills for future work, so that the algorithm would gradually push them out of the production cycle.

And this would give rise to a situation of indirect discrimination, in the sense given to the term by the very definition of indirect discrimination contained in the legal texts, as for example in Council Directive 2000/78/EC of 27 November 2000 establishing a general framework for equal treatment in employment and occupation [art. 2(2)(b)(i)]: "Indirect discrimination (...) shall be taken to occur unless such a provision, criterion or practice can be objectively justified by a legitimate aim and unless the means of achieving that aim are appropriate and necessary".

In some cases, the algorithm includes correction factors for workers' scores for certain circumstances (Xenidis, 2020). This is the case of Deliveroo's algorithm, which is designed to disregard shift absences due to an accident during the provision of the service or a malfunction of the computer application.

The existence of these correction factors proves that mechanisms for rectifying the algorithm can be articulated without distorting its essential character in the business. It is necessary for these correction factors to recognize and support other situations that may give rise to indirect discrimination against different categories of workers. In those cases where there is an objective justification for differential treatment, such as availability derived from conciliation needs or situations associated with maternity. Therefore, an algorithm design or configuration that does not foresee correction mechanisms for legally protected causes is discriminatory. It cannot be argued that the algorithm must be immutable; following the argumentation of the Bologna Tribunal, it is obligated to consider protected situations as fundamental rights of workers.

But discriminatory biases not only occur in algorithmic classification based on external data. Certain algorithms also include the evaluation of customers as an integral element of workers' scoring. This is the case with the digital platform Glovo, which has established a scoring system for its delivery workers that classifies them based on the efficiency demonstrated in completing recent orders, the provision of services during peak demand hours (internal data), and the evaluation made by the end customer of the delivery worker after each delivery (external data).

Same system as in the Uber platform (Rosenblat, 2017), where customers rate drivers through a star rating system that determines the increase or decrease of their reputation, resulting in more or fewer calls. These systems do harm racial groups due to biases or discriminatory prejudices, and as well harm women due to stereotypes about the non-reliability of women. In both cases it can influence clients' ratings and feed into the overall evaluation of drivers and thus into the calculation of their pay, disadvantaging this groups of workers (Altonji, 1999; Bertrand, 2011). The need to introduce correction factors into algorithms is also evident in these cases.

5. The European framework in no discrimination

The European Union (EU) has established a robust legal structure to uphold equality and non-discrimination principles, rooted in both historical and contemporary legal instruments. The framework aims to foster an inclusive society where all individuals, regardless of background, can enjoy equal rights and opportunities.

The EU legal framework rests on foundational principles of equality, non-discrimination, and equal treatment. Historically, western philosophers like Plato and Aristotle debated these concepts, laying early foundations that would later shape EU law.

But, what is discrimination?, as it has been said, (Latraverse, 2018) discrimination is generally defined as unfavourable treatment of individuals based on prohibited grounds within legally specified domains. And it can be said that there are three specific types of discrimination:

- Direct Discrimination: Occurs when one person is treated less favourably than another in a comparable situation due to a protected characteristic, such as race or gender. Justifications are limited and must be legally authorized or pertain to essential job requirements.

- Indirect Discrimination: Arises when a seemingly neutral practice disproportionately impacts a protected group. Justification requires demonstrating a legitimate aim pursued by necessary and appropriate means.

- Harassment: Defined as conduct that undermines a person's dignity and creates a hostile or offensive environment. A single incident may suffice to constitute harassment

The general principle of non-discrimination in EU law finds expression in a set of primary and secondary legal provisions protecting people from discrimination based on their sex, race or ethnic origin, disabilities, religion or belief, age and sexual orientation. Nationality is protected in certain areas of EU law too.

As Primary Law, the Treaty on European Union (TEU) and the Treaty on the Functioning of the European Union (TFEU) establish equality as a core EU value, mandating policies to combat discrimination and promote social justice.

As Secondary Law, several EU directives specifically address non-discrimination in employment, social security, goods and services, and more, with notable milestones: 1974 Social Action Programme and Directive 75/117, focusing on gender equality in pay; Directive 2000/43 and Directive 2000/78, which prohibit discrimination based on race, ethnicity, disability, age, religion, or belief, and recent additions like Directive 2023/970, advancing gender pay transparency.

The personal scope of these provisions covers workers (Directives 2006/54/EC for the ground of sex – hereinafter the Gender Recast Directive, Directive 2000/43/EC for the ground of race or ethnic origin – hereinafter the Race Equality Directive and Directive 2000/78/EC for the grounds of disabilities, religion or belief, age and sexual orientation – hereinafter the Employment Equality Directive). In the case of sex (Directive 2004/113/EC – hereinafter the Gender Goods and Services Directives) and race or ethnic origin certain cases (Race Equality Directive 2000/43/EC) consumers and service providers are covered too. The material scope of the EU general principle of non-discrimination therefore spans the labour market, where the protection is at its widest, and the consumption market, where it is more limited.

As can be seen, the first and most extensive field in which EU non-discrimination legislation has been deployed is employment and labour relations.

Historically, the principle of equal pay, now enshrined in Art. 157 TFEU and Article 4 of Directive 2006/54/EC, foresees that women and men should be paid equally when performing equal work and work of equal value (Barzilay, 2017; Kullman, 2018).

Another configuration of the general principle of non-discrimination is its translation into a prohibition of discrimination on grounds of gender (Gender Recast Directive 2006/54/EC), race and ethnic origin (Race Equality Directive 2000/43/EC), disability, sexual orientation, religion or belief and age (Employment Equality Directive 2000/78/EC) in recruitment procedures, promotions, working conditions and professional training. Hiring and promotion procedures perhaps illustrate best the risk algorithmic decision-making poses regarding the perpetuation of inequalities.

It is necessary to apply this broad scope of regulation to the new reality of algorithmic work in employment relations, but this must not lead to a limitation or undervaluing of non-discrimination regulation. Algorithms cannot be subjects outside of anti-discrimination policies and guidelines.

6. Conclusions.

Algorithms applied to the workplace are an unstoppable reality in today's labour market. It is not possible to go back to previous work structures in which decision making was done exclusively by people.

Therefore, the objective now, with a view to fully respecting the equality rights recognised in the European legal framework, must be to establish systems for monitoring algorithms to ensure that they are unbiased. Clearly, it cannot be assumed that the absence of bias will be the voluntary choice of programmers, especially when, as has been pointed out, many of the biases present in the algorithms are unintentional biases. The fact that decision making by an algorithm is based on previous experience embedded in the algorithm by the programmers is itself a risk of bias.

Transparency, highlighted by the Directive as a basic measure to control bias, is therefore essential.

As stated in the Directive, the use of Artificial Intelligence in employment decisions must be understood as a high-risk use, and as such, it must be subject to strict controls due to the impact it may have on the rights and interests of workers. The difficulty arises in finding ways to reconcile the general interest in the control of algorithms with the interest of the companies that use them in maintaining professional secrecy as a way of remaining competitive.

This is the challenge facing the implementation of the Directive itself and of the Member States' legislation on the subject.

Artificial Intelligence has the potential to transform society for the better, but also to cause irreparable damage if used without the necessary safeguards and controls. It must therefore be ensured that it is a development that remains at the service of humanity, preserving fundamental values and rights.

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