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ALGORITHMIC BIAS IN RECRUITMENT: A MULTIDISCIPLINARY FRAMEWORK INTEGRATING HUMAN BEHAVIOR, INFORMATION SYSTEMS, AND EMPLOYMENT LAW

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ABSTRACT

Algorithmic tools are used to filter, rank, and shortlist job candidates, which has raised concern that algorithms may perpetuate and reinforce recruitment law's intent to prevent bias. Much of the research in this area has been confined to the boundaries of disciplines, and each discipline has viewed bias as existing in the domain of that discipline. This paper proposes that algorithmic bias is more properly viewed as an emergent phenomenon with the algorithm and its effect on the human user, designing the system, and legal liability, and that a disciplinary approach is therefore ill suited for the diagnosis and regulation of algorithmic bias. It brings together the three viewpoints in a lifecycle approach that traces their involvement throughout the algorithmic recruitment process, from algorithm design to data, to deployment, human override and feedback and most importantly where none of the three is present. The comparison of the United States and the United Kingdom, two very different regulatory architectures, shows that most of the time stages are co-governed, the coverage is not complete, and gaps exist both within and between the two architectures, most notably where accountability is not assigned.

KEYWORDS: Algorithmic Bias; Recruitment, Employment Discrimination, Disparate Impact, Title VII, Equality Act 2010, Automated Decision-making, Algorithmic Fairness.

INTRODUCTION

Algorithmic tools are being employed to screen, rank and shortlist candidates at scale (Raghavan et al., 2020). In addition to their benefits in efficiency, there is a persistent concern that such systems may also perpetuate or, sometimes, exacerbate the bias they are intended to mitigate, especially in the areas of race and gender (Raghavan et al., 2020). Studies on this problem have tended to be discipline specific, with behavioural studies focusing on cognition and human–machine interaction, information systems research focusing on bias in data, feature selection and model design, and legal scholarship focusing on doctrines of discrimination and data protection. Both views appear to show just a section of the issue.

This paper proposes that bias in algorithmic hiring is more like a property of the whole system, rather than a property of any individual layer, consistent with the arguments that fairness is not separable from the social context of a system (Selbst et al., 2019). It therefore constructs an integrative model of the genesis and spread of bias throughout the recruitment process; in this regard, it compares the gaps in the framework to those of the United Kingdom, where the implementation of the Data (Use and Access) Act 2025 (legislation.gov.uk, 2025) is relatively new and is being implemented in a rather disjointed way, and the United States – where the gaps are found in older federal statutes and implementation is largely decentralised.

1. LITERATURE REVIEW

2.1 Human Behaviour

It is easy to think of human judgment as a way to correct algorithmic bias, but the behavioural evidence works in two ways. First, a large portion of algorithmic bias is of human origin; algorithms are developed from historical hiring patterns, and the labels used to encode "success" can be biased (Barocas & Selbst, 2016). Second, the human control that is supposed to be a safety factor seems lax. Research on algorithm-in-the-loop decision making indicates that humans fail to consistently identify and correct errors or unfair outputs, and that their engagement with the model can vary within and between groups (Green & Chen, 2019). When thinking about legal safeguards below, it would also seem that a requirement for a human "in the loop" would be allowing, instead of solving, the issue of biased outputs (Green, 2022).

2.2 Information Systems

Often, bias is framed as a problem with the data that can be fixed with a “cleaner” data set, or a problem with the model which can be fixed with a more “fair” model. This underestimates the issue in two ways. The point of entry for biases in the pipeline could be many, including the definition of the target variable and the training data, as well as the use of proxy attributes that correlate with protected attributes (Barocas & Selbst, 2016). Broadly, "de-biasing" is not a purely technical process: empirical evidence shows that there is no way to simultaneously satisfy multiple notions of fairness; any design is an assertion of a specific opinion about what unfairness to accept (Kleinberg et al., 2017). Solutions that do not reflect fairness can also fall short when the model is implemented in their social context (Selbst et al., 2019; Suresh & Guttag, 2021).

2.3 Employment Law

2.3.1 Employment Law: the United States

US anti-discrimination law is based on older federal laws: Title VII of the Civil Rights Act 1964 (U.S. Equal Employment Opportunity Commission, 1964) (race, colour, religion, sex, national origin, extended to sexual orientation and gender identity by Bostock v. Clayton County, 2020) (Supreme Court of the U.S, 2020); the Age Discrimination in Employment Act 1967 (U.S. Equal Employment Opportunity Commission, 1967) (applicants aged 40 and older); and the Americans with Disabilities Act 1990 (U.S. Department of Justice Civil Rights Division, 1990) (disability and reasonable accommodation). While all three lead to algorithmic hiring via disparate-impact and related theories, the business-necessity defence, which is available when a practice predicts job performance, that is what a hiring model is designed to do, could allow it to become a justification for the very correlations that are currently debated. (Barocas & Selbst, 2016). The court is now testing their application to vendor tools in the Mobley v. Workday case, where it granted preliminary certification of a nationwide age discrimination class action against an AI screening program that allegedly discriminated against older applicants as an "agent" of the employer (U.S. Equal Employment Opportunity Commission, 2024). However, the accountability layer is not in sync: The federal guidance on AI hiring was scrapped in 2025, although some sub-federal guidance has diverged (Local Law 144 in NYC requires independent bias audits of automated employment tools and California's final rules include notice, risk-assessment, and human review requirements (California Privacy Protection Agency, 2024); a federal impact-assessment bill is still pending (Congress.gov, 2025). The same tool can then be a law violator in one city, a law-abidor in another and an unregulated item in the federal arena.

2.3.1 Employment Law: the United Kingdom

The United Kingdom has more cohesive architecture. Indirect discrimination under the Equality Act 2010 is forbidden, unless it can be demonstrated to be a proportionate way of accomplishing a legitimate aim (a defence similar to that of the US business necessity, albeit with the added danger of being taken to be a method of achieving a legitimate aim). For data protection, the Data (Use and Access) Act 2025 (legislation.gov.uk, 2025) allows for only Automated decisions, with safeguards such as meaningful involvement by humans, and the Information Commissioner's Office (ICO) has provided guidance on fairness, transparency and bias for recruitment (Information Commissioner's Office, 2024). The contrast with the United States is therefore one of form rather than of function, there is one national regulator, one equality statute in Europe; multiple in the United States; but both rely on defence based on proportionality, and rely on human oversight as well, and both leave the same gaps as demonstrated by the structure of the framework.

2. AN INTEGRATED LIFECYCLE FRAMEWORK

The three lenses are usually focused on the same object, but at a fixed angle; like the impartial tool in a rod-and-stick, sitting at a certain angle waiting for the person who will be disciplined. This is done to treat bias as distributed across the recruitment process, and co-owned, rather than just a question of which discipline owns this? And what parts of the process does no single discipline see? The matrix below illustrates six lifecycle stages across the three lenses: If a lens is considered to be active in a lifecycle stage, it is shown in a filled cell; if it is considered to be silent, it is shown in a blank cell.

Stage	Human behaviour	Info. systems	Employment law
Design	biased targets	target choice	—
Data & labels	historical bias	proxy features	—
Model	—	metric conflicts	adverse impact
Deployment	automation bias	context mismatch	ADM safeguards
Human override	weak oversight	—	'meaningful' role
Feedback loop	—	self-reinforcing	—

Figure 1: Bias Lifecycle. Note: Filled cells indicate stages ordinarily engaged by each lens; blank cells indicate stages that fall largely outside a lens's habitual scope. The

mapping is the author's own synthesis, drawing on Barocas and Selbst (2016), Green and Chen (2019), Green (2022), Kleinberg et al. (2017), Selbst et al. (2019), Suresh and Guttag (2021), Title VII of the Civil Rights Act 1964, the Equality Act 2010, and the Data (Use and Access) Act 2025.

Two features of the mapping carry the argument. First, the majority of stages are co-governed. At the model stage, for instance, there is a choice among mutually incompatible fairness criteria, which is both technical (Kleinberg et al., 2017) and legal: the criterion chosen determines how a system is exposed to a disparate-impact or indirect-discrimination claim; treating it as purely technical conceals its legal importance, and treating it as purely legal conceals that no description is neutral. Second, and more importantly, there is uneven coverage. The feedback stage, in which hiring results feed into the training data and reinforce previous hiring patterns, is visible to information systems, but lacks emphasis in doctrines designed for discrete decisions, and is hidden to monitoring mechanisms that only act at the time of a hiring decision.

The framework works in these spaces. At the override level, both systems rely on meaningful human intervention (UK Data (Use and Access) Act 2025) (legislation.gov.uk, 2025) and human review (California's automated decision-making rules), but there is evidence that human reviewers are not consistently effective at detecting or correcting biased outputs (Green & Chen, 2019; Green, 2022). If that is the only safeguard used as a compliance strategy, then it may be compliant but not behaviourally compliant, both in the UK and globally. However, a "de-biased" model that is technically unbiased (Selbst et al., 2019) can nonetheless produce adverse impact when it is integrated into a recruiter's workflow. On this account, bias is emergent; that is, it is created and propagated by the dynamics of the interaction between the layers; an intervention limited to a single layer can be neutralised or displaced by another layer.

The role of the framework is thus in the diagnosis and not in prescription. It makes the co-governed stages and between-lens gaps explicit, which points to where single-discipline interventions are likely to fail, and where accountability is not allocated, from which a basis for governance is developed that is not just for catching something at one point in the system, but also for governing it through the system.

3. IMPLICATIONS

The framework has three implications for governance as a diagnostic tool. First, it implies that a bias audit at the model stage is not enough, bias can occur at the design, override, or feedback stage, and a model audit will not detect that; a bias audit scope should cover the entire life cycle, which is what Local Law 144 in New York City (NYC Consumer and Data Protection, 2021), for instance, does, it institutionalises exactly this type of limited model audit. Second, it poses the question of accountability differently, as a problem of allocation of responsibility at various stages of a system, rather than as a question of fairness, and reveals the feedback loop as a point in the system where responsibility is not clearly assigned. Third, it suggests that protection based on human participation is not enough to rely on as a standalone legal protection and must be validated by a behavioural safeguard (Green & Chen, 2019).

4. CONCLUSION, LIMITATIONS AND FUTURE WORK

This paper has contended that algorithmic bias in recruitment should be seen less as a problem with the algorithm itself than as an emergent property of the complex interplay between the behaviour of the user, the design of the system, and the legal accountability for the system. This paper has also proposed a lifecycle framework for making this interaction analysable. The narrative is speculative, and the main statements are yet to be tested empirically. The generalisability of the tool is limited to two common law jurisdictions, with extension to civil-law regimes (e.g. those covered by the EU AI Act) being a future step, and the application of the tool to a specific hiring system also being for future research.

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