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**The Role of Artificial Intelligence in Staffing: An Evaluation of Fairness and Ethical  
Implications for Candidate Selection**

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**Abstract**

**Purpose:** AI utilization has seen an increased adoption in the recruitment processes of organizations, hailed mainly for its ability to reduce time and effort in manual and repetitive tasks.

**Methodology:** The recruitment process witnessed significant changes, with further automation in resume collection, screening and even candidate shortlisting. An online survey was employed with 160 HR professionals from diverse industry sectors and a quantitative, deductive approach was taken, analyzing data with SPSS (descriptive statistics, correlation, regression). While AI is gaining popularity, the research reveals the risks associated with reliance on algorithms, primarily in the form of bias. Whether stemmed from the coding process, or in the process of machine learning that amplifies a slight bias, the study illustrates the various touch points to particularly consider in mitigating the risks of AI-driven bias in recruitment.

**Results:** AI-based staffing has a positive effect on unbiased and ethical selection ( $\beta = 0.957$ ,  $p < 0.001$ ) and staffing efficiency ( $\beta = 0.816$ ,  $p < 0.001$ ). But, the relationship between AI-based staffing and staffing efficiency was not mediated by unbiased and ethical selection ( $\beta = 0.002$ ,  $p = 0.992$ ). Existing studies on AI, recruitment, and biases provide the necessary background in drawing links between bias and the efficiencies of AI in the recruitment processes. The study hypothesizes that AI provides unprecedented efficiencies in standardizing processes, optimizing time and allowing recruiters to focus on more strategic decision-making. However, the study also reveals the risks of AI bias, whether from the coding stages of the algorithm or the clinically objective nature of the screening process that could unintentionally eliminate valid and eligible candidates.

**Unique Contribution to Theory, Practice and Policy:** Theoretically, it explains how the link between AI and efficiency does not go through ethical selection. As a practical solution, it suggests using the combination of human-AI model. It calls for policy recommendations of ethical guidelines and audits.

**Keywords:** *Artificial Intelligence, Recruitment, Selection, Staffing, Efficiency, Recruitment Bias, Ethical Recruitment*

**JEL Codes:** *J23, J24, M51, O33*

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## INTRODUCTION

Recruitment is a key step in the identification and hiring of the right resources to conduct the necessary tasks within an organization. The quicker a position is filled, along with the quality of work the new employee does in respect to the vacancy, the higher the business continuity of an organization to achieve its objectives. Parameters of a successful recruitment include the lead time needed to fill a vacant position, the cost associated with the recruitment process and the success of the hired employee in delivering the job description of the role. Technological evolution meant the adoption of digital solutions in the recruitment process in aims of increasing accuracy, reducing time and resources and filling the vacant role with the right candidate.

While each company conducts subtle differences in the way they recruit, the general process is very similar. The Human Resources department is responsible for a wide array of tasks, including the recruitment of staff in an organization. The process begins with the recruitment objectives such as defining what position needs to be filled, the retention rate expected, diversity range of hires among other factors (Karim et al, 2021). A recruitment strategy is then developed to identify the recruitment sources, timeline and how to communicate the position. Moreover, the recruitment activities follow, executing the strategy by pursuing the recruitment sources and, if needed, external recruiter support (Karim et al, 2021). As applications are submitted, the recruiters then review, shortlist, interview and select the candidates, concluding the recruitment process with a job offer and signed contract.

Recruiting traditional is a time-consuming and, for the HR team, a largely manual process. This entails reviewing the submitted resumes, filtering through the candidate pool, conducting interviews and evaluations for the most suitable candidate depending on the job role and description. Technological advancements helped the automation of many processes, saving time, effort and resources to complete. Application tracking systems (ATS) became a popular practice among companies worldwide, which reduced the average 23 hours of screening time to an automated method estimated at 1 hour (Piecheva, 2023). The capabilities of ATS are continuously evolving, as it helps in the tracking of jobs posted, candidates that applied, filtering of the submitted resumes and even help in the scheduling of interviews (St-Jean, 2022). Given that most recruiters should track the lead time needed for the whole recruitment process from the identification of the vacancy to having an employee fill the position, the use of technological tools help increase efficiency and reduce the wait time for an employee to be hired (Solek-Borowska and Wilczewska, 2018).

Artificial Intelligence (AI) further transformed the capabilities of recruiters, providing a much more streamlined approach in having an exponentially shorter turnaround time for selecting, evaluating and hiring candidates (Nawaz et al, 2024). A core advantage of AI is its “natural learning algorithms” and natural language processing capabilities (Nawaz et al, 2024). The continuous learning of the system and its capability of identifying, understanding and comparing the preset criteria in the role profile makes AI uniquely beneficial to customize the guidelines as needed and get accurate results. When applied to the recruitment process, the AI-powered systems within a company can filter through many candidates’ resumes in a matter of few seconds, filtering those with the highest match to the job role description and established criteria by the recruitment team.

There are several studies that address the role AI plays in the recruitment process of organizations, such as Karaboga and Vardarlier (2024), Meshram (2023) and Lundvall (2022). However, these studies lack the depth and do not address the ethical considerations and mitigated measures in a comprehensive analysis.

Ethical risk comes because of the qualitative difference between rule-based ATS (keyword matching) and machine-learning AI (predictive modelling). Machine-learning algorithms, unlike deterministic keyword filters, learn patterns from past hiring data and create models that can inadvertently reinforce existing hiring patterns, and are often considered a "black box" that is difficult to explain. In this way, the same predictive power that results in unprecedented efficiency, also creates hidden, self-contained sources of discrimination, which are different from earlier, more transparent and easily understood automated screening.

### **Problem Statement**

Finding the right candidate is often challenging and a time-consuming effort that, if delayed for long, can disrupt the business continuity of the company. An ethical issue with the traditional methods of recruitment stems in the risk of bias from the recruiter, which could lead to an inconsistent approach in evaluating the candidates, subsequently resulting in inefficiencies. AI provides a quicker and more objective approach to recruitment, providing accurate job matching with candidates. However, recent studies indicate that AI-powered recruitment solutions also result in unintentional bias (Chen, 2023). Whether at the coding stage or in the machine learning of the algorithm, the bias also poses further challenges in the rationale of decisions taken. In other words, there is a lack of transparency as to why the AI program made certain shortlisting decisions (Chen, 2023).

Moreover, given the large volume of personal data handled by AI programs in recruitment, it further poses ethical challenges such as data privacy and security. While there are stringent regulations in place on how to handle and protect such data, a slight compromise can result in major security breaches. It is therefore critical to understand the risks, along with the benefits, associated with the adoption of AI in recruitment. Also important to identify effective mitigative measures, considering the degree of human oversight needed, to ensure a fair, transparent and reliable recruitment system utilizing AI programs.

Without having a transparent and clear understanding on the risks of AI use in recruitment, organizations face the challenge of overreliance on automated procedures that may yield biased and inaccurate recruitment decisions, which will have a negative impact on the overall performance of the organization.

The lack of transparency, even within the minds of its creators and users, is a large part of the issue in the context of AI-driven recruitment processes, known as the "Black Box" phenomenon. Unlike humans, who may have a clear, documented reason to implement a shortlist, deep-learning systems rely on thousands of variables that are passed through hidden layers, generating shortlists without explicit and audit-worthy explanations (Chen, 2023). This presents a basic conflict: while organizations can use AI for efficiency, the algorithms can have considerable legal and ethical implications if not transparent. If the outcome is unfair because of some of the criteria used, the

company will still be subject to employment laws, but won't be able to explain, challenge or correct the algorithm's decision making process, and will be vulnerable to regulatory action and damage to its reputation.

## **LITERATURE REVIEW**

### **AI-based Staffing with Unbiased and Ethical Selection**

Many authors support AI in its ability to be objective in evaluating resumes, reducing the risks of nepotism and favoritism as well as reducing the overall human bias in decision making (Seppala et al, 2024; Albaroudi et al, 2024). Studies addressing the risks of unfair and preferential treatment for candidates show that the hiring decisions are usually not optimal for the organization, nor are selected candidates the most suitable for the job (Chen, 2023). Consul et al (2021) describe the risks of unconscious bias in recruitment, where the selection process is not based on intentional acts of favoritism or dismissal; the authors add that unknowingly biased recruitment risk building a dysfunctional team that may not be able to work effectively together, in turn compromising the quality of work conducted. While the authors specify on the private radiology sector, the principle can logically be applied across industries and companies. Similarly, Pandey dives deeper on the subject, illustrating unconscious bias accounting for over 8% of recruitment decisions, with mitigations such as increased awareness and trainings to minimize such outcomes (2021). One of the potential solutions has become the integration of technological solutions, naturally developing into AI-powered systems to support the recruitment process (Polli, 2019). Stripping the recruiter's inherent biases is seen as an instrumental step to having an objective approach in screening and selecting candidates (Polli, 2019).

AI is often recommended for its naturality of analysis, which mitigates the risks of human biases; many of the articles supporting the objectivity of AI have two common assumptions. First, they assume that human decisions are subconsciously biased, and AI holds the potential of mitigating with discriminatory decision making in the recruitment process (Seppala et al, 2024; Ul Oman et al, 2024). The second is to convey AI as the solution to human bias due to the mechanical approach of systems regardless of applicants, their backgrounds and other factors that may be discriminated against by human recruiters. This second assumption is too generic and does not address the risks of AI-generated bias, which poses its own set of challenges. Given that AI is relatively new in its widespread implementation, particularly in the recruitment process, there is little research done on the prevalence and severity of AI hiring bias. This gap in the literature poses a significant risk in the conclusions derived about the benefits of AI and its supremacy in terms of objectivity in comparison to human decision making.

Chen (2023) provides insight on the various types of AI bias that can unintentionally impact the decisions made. Chen explains how the statistical discrimination theory, a "prejudice from assessment criteria that generalize group characteristics to individuals" (Tilcsik, 2021), has developed into algorithmic bias, which is the "systematic and replicable errors in computer systems that lead to unequal and discrimination based on legally protected characteristics, such as race and gender" (Jackson, 2021). These are critical factors to be considered for AI use in the recruitment process, which is often missed, such as the case by authors like Ul Oman et al (2024),

Albaroudi et al (2024) and Seppala et al (2024). Making a general assumption that AI is objective overlooks the algorithmic bias that could skew the evaluation findings in favor, or against, certain groups of people, ultimately resulting in an unfair hiring decision (Chen, 2023).

The history of content moderation indicates the increased reliance of online platforms on the use of algorithmic intelligence in controlling online interactions (Gorwa, Binns, R& Katzenbach, 2020). Early days of the internet relied on moderation that was largely manual - human moderators went through the posts and deleted content that did not conform to societal regulations.

Fundamentally, AI-based moderation is implemented based on three technologies that interact with each other: machine learning, natural language processing (NLP), and computer vision (Ami, 2021). Machine learning models are trained on large volumes of labeled data, posts, images, or videos that are identified as harmful or benign. Through these models, statistical correlations are learned which enable them to forecast whether new unseen content is to be flagged. NLP allows systems to read between the lines, identify hate speech, and other potentially dangerous phrases whereas computer vision algorithms can detect nudity, violence, or other graphic material in pictures and videos. These systems are becoming more and more capable of carrying out real-time evaluation of billions of data points on a daily basis as they grow.

Nevertheless, AI moderation is fast and highly advanced at a price. The algorithms tend to carry the bias in their training data, which leads to unequal application to different languages, cultures, and socio-political contexts (Draude et al., 2020). An example is that the automated systems which have been trained in English-language related datasets are more likely to fail in non-western languages, which puts the young people around the world unequally in terms of protection. Moreover, AI decision-making also poses a challenge of explaining or challenging the results of moderation due to its inherent opaqueness, the so-called black box problem. Once the material of a youth has been deleted mistakenly or harmful content has been unnoticed, the process of attributability turns into a complicated one that matches human regulation with the freedom of control by machines.

The second important aspect of AI moderation is the abdication of moral judgment onto computational logic (Udupa, Maronikolakis & Wisiorek, 2023). The algorithms are crafted to operationalize such notions like harmful, inappropriate, unsafe, but all these are normative categories based on social and cultural values. With more and more platforms basing their decisions on predictive algorithms in order to establish what is considered harmful to the youth, the ethical and epistemological underpinnings of those choices are called into question (Perez Vallejos et al. 2021). Such outsourcing of moral judgment to computers in real life is potentially dangerous in that it could reduce moral judgments to probabilistic computation unaccompanied by human compassion and understanding of context. It also questions the idea of democratic legitimacy of the digital governance because corporates rather than public institutions determine and implement moral boundaries in the online environment.

In organizational terms, the human to AI moderation has resulted in new human and AI moderation forms of labor and control (Ruckenstein & Turunen, 2020). Although AI systems screen in large numbers, there are borderline or escalated cases that human moderators still screen in large

numbers, usually in psychologically challenging circumstances (Subrahmanyam, 2025). The combination brings up ethical issues of algorithmic exploitation of labor, mental health risks, and the invisibility of human labor behind automated systems. Additionally, the increased reliance on algorithmic solutions can be seen as an incentive to corporations that would focus on efficiency and brand safety, rather than user well-being and participatory transparency (Cheong, 2024).

In the case of youth protection, AI moderation comes with certain opportunities and threats. On the one hand, it allows the platforms to quickly eliminate explicit sexual content, grooming efforts, or violent content that may traumatize minors (Odudu, 2024). Alternatively, algorithmic filters may categorize educational, artistic, or advocacy material concerning sexuality, mental health, or identity as misinformation and therefore muting potential discussions that enhance youth development (Pellegrino & Stasi, 2024). The conflict between the protection of the young users and the maintenance of their digital freedom is still a characteristic problem of the moderation ethics of the modern age.

This development is further complicated by the policy environment that prevails globally. Various jurisdictions have different expectations of the platforms. The Digital Services Act of the European Union (DSA) requires transparency and accountability to automated moderation, whereas the United States uses the Section 230 of the Communications Decency Act to protect the platforms against liability based on user-created content (Frosio & Geiger, 2023). Conversely, the growing trend is a paternalistic model of regulatory practices found in countries of Asia and Middle East with emphasis on moral protection and social harmony. Such plurality of expectations of the law highlights the geopolitical disintegration of AI regulation and the cultural formation of understandings of harm, responsibility and protection of youth (Turdialiev, 2024).

Finally, AI-based content moderation is an impressive reorganization of digital power. It shifts the power of decision-making to dark algorithmic systems that are managed by privately owned corporations and away from individuals and human moderators (Parmar & Murari, 2025). With these technologies constantly under development, they will not only delimit the boundaries of online expression, but will also shape the ethical structure of the online public space. Knowledge of their operation and development is, hence, necessary to evaluate the extended consequences of legal accountability and ethical responsibility in protecting the youth against digital abuse.

***H1: AI-Based Staffing significantly impacts Unbiased and Ethical Selection.***

### **AI-based Staffing with Staffing Efficiency**

Recruiting the right candidate to match the specific job roles is a time consuming and difficult task, which impacts both the efficiency of the Human Resources team as well as the overall performance of the organization (Verdapradha et al, 2019). HR departments around the world have increasingly relied on technological solutions to expand their reach, refine their search and streamline the overall recruitment process (Lundvall, 2022; Vedapradha et al., 2019). While some studies highlight the benefits and needs of using AI in recruitment, such as Ludvall arguing the shortage in the labor market makes AI necessary to optimize hiring (2022), others focus on the willingness of the organization to adopt technological solutions and external laws and regulations on how these tools could be used (Thakur et al, 2023). There are different ways that AI could be utilized in

reducing manual labor, lead time needed for completing tasks and provide strategic insights based on big data analysis (Abdelraouf, 2024). Many applications of AI have proven to reduce time and errors without compromising on the accuracy and quality of results (Abdelraouf, 2024). Significantly cutting down the lead time needed to scan through hundreds of resumes and filtering those with the relevant skills, experiences and background for a vacant position from several hours to a matter of minutes not only saves the recruiters time but also allows them to focus on more strategic tasks and decisions. Therefore, the staffing process with AI-enabled tools expedites manual tasks and optimizes business continuity for the organization in filling the job roles needed to deliver on its operational and strategic objectives (Rathore, 2023). Regardless of the hypotheses of studies, the automated and high computational capabilities of AI is viewed widely as instrumental for optimizing efficiency and speed in many steps of the recruitment process.

While most of the published literature hail the benefits of AI to optimize efficiency, reduce time and maximize accuracy, there is limited research to quantify how AI-based recruitment compares with human ones. Further, Wright and Atkinson (2021) describe the willingness of companies in integrating AI solutions as one of the determining factors on whether efficiencies are realized in the recruitment process. Companies may understand the benefits of AI and other digital solutions in the hiring process but refuse to adopt these technologies as they consider recruitment to be a human activity (Wright and Atkinson, 2021). Similarly, the position being recruited impacts the likelihood of using AI and if so, the extent of reliance on automated tasks; Wright and Atkinson found in their primary research that C-suit positions are more likely to be hired by recruiters, with minimal AI use, while fresh graduate positions are more automated (2021). There is little research to support the role a vacancy's seniority plays on the extent of automation and AI-reliance in the recruitment to evaluate the credibility of Wright and Atkinson's theory.

### ***H2: AI-Based Staffing significantly impacts Staffing Efficiency.***

#### **Unbiased and Ethical Selection between AI-Based Staffing and Staffing Efficiency**

The efficiencies realized by AI use in the recruitment process make it highly desirable by companies to reduce cost, time and ensure standardized performance (Mupaika and Yadav, 2024). The risks of bias in human decisions are assumed as mitigated by the digital solutions of AI-powered recruitment systems (Charkra et al, 2024). This further motivates organizations in adopting AI in the recruitment process, with varying degrees of implementation. Most of the literature reviewed focus on the efficiencies AI has in terms of processing large volumes of data in a quick turnaround (Mupaika and Yadav, 2024; Abdelraouf, 2024; Lundvall, 2022). This is beneficial for recruiters to dedicate their efforts in quality controlling the findings of AI and making more strategic decisions (Charkra et al, 2024). With AI-enabled recruitment, the relevant employees are capable to dedicate the necessary time and effort in having oversight at deeper issues, addressing ethical and biased risks from the generated recommendations and outcomes. Therefore, mediating the efficiencies in the recruitment process with selective AI usage means reducing the manual hours and effort needed by recruiters to provide human oversight and review to ensure the risks resulting from overreliance in AI can be mitigated. This is a logical reasoning gathered from varying studies rather than dedicated research to find the correlation between efficiencies and their role in reducing biased recruitment.

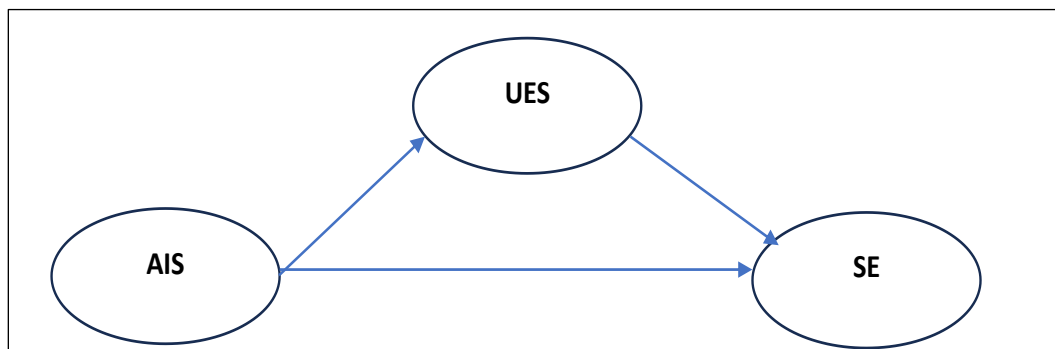
On one hand, studies are promoting the objectivity of AI technologies to reduce the human bias in the recruitment process (Lundvall, 2022; Polli, 2019). Streamlining the process into standardized actions eliminates the risk of having human error or any type of preferential or subjective treatment between applicants. On the other hand, the bias that stems from the coding of the AI algorithm risks amplification in discriminatory decisions by the software (Hunkenschroer and Lutge, 2022). Studies warn of the risks on either side, with a brief statement or advice that a balanced approach is important. However, there is a lack in dedicated literature about the role AI-enabled efficiencies have on ensuring unbiased selections. Consequently, the findings for this hypothesis are based on deduced conclusions rather than a particular study to rely on empirical findings.

***H3: Unbiased and Ethical Selection mediates the relationship between AI-Based Staffing and Staffing Efficiency.***

### Conceptual Framework

The theoretical framework illustrates the relationship between the independent variable, mediator and the dependent variable.

- Independent variable: AI-based Staffing (AIS)
- Dependent variable: Staffing Efficiency (SE)
- Mediator variable: Unbiased and Ethical Staffing (UES)



*Figure 1: Research Variables*

### Underpinning Theory

Given the widely researched topic of AI implementation, and its applicability within the recruitment process, there are multiple theories that should be considered.

First, the algorithmic decision-making theory is commonly referred to when assessing the AI's algorithms being capable of machine learning and delivering tasks such as screening resumes, ranking the candidates and predicting the successful hire of candidates based on historical hiring data. Moreover, the fairness and bias theory is useful in understanding the extent of which AI recruitment systems factor ethical concerns into its decision making. This is an instrumental theory in assessing the extent of bias that AI may produce in its results, along with deeper insight on the sources of ethical concerns that reliance on AI could yield.

Another relevant theory for the research is the Technology Acceptance Model (TAM), which gauges the extent of AI recruiters, and the organization is comfortable in adopting in its decision-making processes (Almeida et al., 2025). The TAM provides valuable input on the reasons why some companies are more willing than others to realize the benefits of AI in recruitment as well as identify a clearer correlation between AI-enabled recruitment and likelihood of biased and unethical selections.

Implementation of artificial intelligence in content moderation raises complicated questions regarding the lawfulness responsibility, particularly when human oversight and error are eliminated by making a decision, or making a mistake, with no human input (Banchio, 2024). Conventionally, the moderation outcomes were attributed to human decision-makers that occupied a low-level in the platform hierarchy. But since algorithmic systems are taking the position of operational control in determining, erasing, or marking digital content, the line of liability is becoming more blurred. The underlying legal issue is whether the developer, the platform, the AI system itself or the regulatory environment in which the algorithmic errors take place is responsible to compensation damages caused by the errors.

The core of such a debate is the principle of intermediary liability that is used to establish the legal liability of the platforms as a result of hosting such content (Buiten, De Streel, & Peitz, 2020). Most western jurisdictions have provided intermediaries with conditional immunity against liability due to user-generated content, on the condition that they take timely action to have illegally created content removed when they are notified. This framework was developed in a period of manual moderation and has been shown as an insufficiency in terms of answering algorithmic governance. AI-based moderation is a preventive measure, eliminating large amounts of content before human beings can set their eyes on it, effectively turning websites into agents of censorship instead of mere mediators of online communication (Ami, 2021). This is a radical change to the premise of intermediary immunity because platforms now have a curatorial role, which has implicit moral and legal responsibilities associated with it.

Furthermore, in cases where algorithmic systems unreasonably block legitimate expression or they do not filter harmful material directed at minors, the current legal principles in place do not tend to have the specificity to lead to the attribution of responsibility (Volkov, 2025). The lack of transparency of AI systems, that is, the impossibility to understand the decision-making process of the system, gives rise to evidentiary obstacles in cases where the victim needs redress. In case a teenager gets access to violent or exploitative content that managed to bypass AI filters, or a youth-focused advocacy page is unfairly deleted, then who is to answer when no human-based decision-maker can answer why the system acted the way it did? In these situations, common ideas of negligence, intent or foreseeability become meaningless. The concept of algorithmic accountability therefore requires new frameworks of interpretation that describe distributed and non-human agency of AI systems (Beckers & Teubner, 2023).

Due to these problems, a number of jurisdictions are starting to trial new types of algorithmic liability. These frameworks seek to apply the current product liability and negligence principles to algorithmic harm (Pfeiffer, 2023). In a case like that, the company using AI-based moderation tools may be liable in case it did not use due diligence in training, auditing, or overseeing the system.

This strategy puts an emphasis on the organization as responsible, not on an individual desire, but on structural design errors, ineffective control, or intransparent business operations as major causes of algorithmic harms. Nonetheless, opponents say that algorithmic liability has not yet been developed conceptually or practically, particularly in transnational digital ecosystems.

The Digital Services Act (DSA) by the European Union is one of the most extensive efforts at redefining accountability in the age of AI moderation (Gosztonyi, Gyetván & Kovács, 2025). It has platform transparency requirements where the platform must reveal the way they use automated systems to decide on content, and offer a user an appeal mechanism. Notably, the DSA redefines moderation as a socio-legal role rather than a technical one, which is at the same time mixed with human rights. It aims to reestablish procedural fairness, whereby platforms are required to embrace efficiency and due process, such that users, and minors in particular, are not left to the whims and fancies of algorithms. However, it has been pointed out by critics that enforcement is subject to the goodwill and ability of the national regulators which differs greatly in different member states.

The United States, on the contrary, is stuck in the Section 230 paradigm, which provides widespread immunity to internet platforms. On the one hand, this practice promotes innovation and freedom of expression, but on the other hand, it contributes to the lack of accountability on algorithmic harms. Section 230 protects liability against platforms, so in essence, it enables platforms to roll out AI systems without much legal consequences even when the systems are used to perpetuate bias or do not safeguard vulnerable users (Carman IV, 2024). The reform ideas have come forward, which means that the immunity must be conditional upon provable transparency and algorithmic responsibility. However, any legislative change is met with opposition among the influential technology companies and those who advocate free speech who feel that higher liability might result in the impacts of over-censorship or discourage technological advancement.

There are other challenges that most of the developing countries struggle with besides these contrasting models. Platforms in areas where infrastructures of digital governance are still in the early stages tend to be run with little control, being almost entirely AI-mediated without any contextualization (Duberry, 2022). This dynamic brings up the issue of digital colonialism, in which the norms and algorithms developed by major social media companies with a Western moral ethos are exported to the rest of the world. The absence of culturally adaptive AI systems does not only reduce the legal responsibility, but also propagates epistemic injustice, favoring a set of values over others (Miragoli, 2025). In its turn, this does not allow breaking down the legal discourse of AI moderation into more general issues of power, culture, and epistemology.

The accountability situation is also complicated by the problem of youth protection. The global treaties like the United Nations Convention on the Rights of the Child confirm that children deserve the protection against harmful content, but at the same time, they should have the freedom of expression and the right to access information (Nawaila, Kanbul & Ozdamli, 2018). AI moderation has to, therefore, walk on the fine line between protection and participation. This is because legal systems should specify the line that represents lawful protection and illegal limitation of rights. Excessive filtering can be the violation of informational freedoms, whereas the lack of control leads to psychological damage in the young audience (Pellegrino & Stasi, 2024). The law

therefore is confronted with the impossibility of harmonizing antithetical rights in an automated logic environment.

Another related issue is the transparency of procedures. Moderation outcomes are correctable, and therefore, the level of accountability relies on whether the users and regulators can understand, challenge, and correct moderation outcomes. Nevertheless, the proprietary quality of the AI models does not allow any substantial scrutiny (Wang et al., 2022). The majority of the largest platforms consider moderation algorithms as trade secrets due to a competitive advantage and security considerations. This privacy imposes a sense of accountability vacuum: users have no power to challenge unfair judgments, researchers have no power to look under the hood, and regulators have no power to bring users into line. This type of asymmetry between corporate influence and social control undermines the belief in the computer-based governance and strengthens the belief that AI is an uncontrollable judge of the truth.

The debate on the subject of legal responsibility on this shifting landscape is not merely one of avoiding damage but also re-examining justice within algorithmic cultures. The law should no longer be reactive to the liabilities brought about by AI systems, but proactive in its governance. This necessitates the incorporation of ethics into the juridical landscape of digital governance-enforcing that accountability should not be confined to penal actions but to transparency, equity and active governance. It is only through this change that the law can be reformed in a way that could provide appropriate protection to the youth and a democratic integrity in the era of algorithmic moderation.

Organizational Justice Theory looks at how candidates feel about fairness when it comes to AI-driven processes and what makes them feel the process is fair: procedural justice (consistent rules), distributive justice (fair outcomes), and interactional justice (fair explanations). Candidates agree with algorithmic decisions when they are made in an apparently fair manner but are upset when they are given to a "black box" where they cannot appeal.

The use of AI by the organization conveys strong signals to applicants and is known as Signaling Theory. A lack of transparency in automation signals lack of ethics and lack of fairness, whereas transparent, ethical AI automation signals innovation, accountability and respect, directly affecting application rates and employer brand.

Human Capital Theory considers recruitment as a process of investment which is maximized for the value of employees in the longer period. While AI helps to cut down transaction costs and boost the accuracy of performance predictions, it could also inadvertently leave out candidates who are better suited for innovation, those who possess a more valuable range of skills and knowledge that are not traditional or marketable leaving to the company an under-diversified human capital base.

### **Research Gap and Potential Hypothesis**

While there is extensive literature on the operational efficiency of AI and on the ethical implications of AI and the need for an ethical selection process, there is still no empirical model that tests whether unbiased and ethical selection is a precondition to achieving staffing efficiency through AI, or if unbiased and ethical selection is achieved independently of staffing efficiency.

Current research works on efficiency and algorithmic fairness as separate rather than potentially mutually connected variables as organizations have no empirical evidence to inform them if there is a link between fairness and faster AI.

To fill this gap this study explores the role of Unbiased and Ethical Selection as a mediator between AI-Based Staffing and Staffing Efficiency, testing the following three hypotheses: H1: AI-Based Staffing significantly affects Unbiased and Ethical Selection, H2: AI-Based Staffing significantly affects Staffing Efficiency, and H3: Unbiased and Ethical Selection is a mediator between AI-Based Staffing and Staffing Efficiency.

## METHODOLOGY

The research design adopted is a deductive methodology. The primary data is collected via quantitative research, which will be conducted through surveys shared online, with results from 160 respondents. Stratified random sampling was used for sampling. The survey participants are selected through stratified random sampling within the field of recruitment, dividing the population sample by industry, seniority and other subdivisions from which candidates are randomly selected. The research sample size was 160 participants. Data collected from the surveys was analyzed using SPSS. Data was presented in form of tables.

## FINDINGS

### Descriptive Statistics

Using descriptive statistics, the demographic data of the respondents is presented in a tabular format as found below:

**Table 1: Role**

		Role			
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	HR Officer	44	27.5	27.5	27.5
	Recruitment Specialist	55	34.4	34.4	61.9
	Talent Acquisition Manager	40	25.0	25.0	86.9
	HR Director/Manager	20	12.5	12.5	99.4
	Other	1	.6	.6	100.0
<b>Total</b>		<b>160</b>	<b>100.0</b>	<b>100.0</b>	

As shown in Table (1), in the total number of respondents participated in survey, majority were recruitment specialist (34.4%), and others were HR officers (27.5%) and talent acquisition managers (25.0%). The other 12.5% were HR Director/Manager only .6% were from other category. The distinguishment between talent acquisition and HR roles is to illustrate those who work directly in recruitment activities, while HR personnel may have indirect involvement in staffing. Despite differences in job titles, the participants are within the relevant department and have clear insight on how staffing is conducted in their organization, along with the tools and procedures used.

**Table 1: Experience**

Experience					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than 2 years	42	26.3	26.3	26.3
	2-5 years	59	36.9	36.9	63.1
	6-10 years	40	25.0	25.0	88.1
	More than 10 years	19	11.9	11.9	100.0
	<b>Total</b>	<b>160</b>	<b>100.0</b>	<b>100.0</b>	

As shown in the above Table (2), most of the respondents were well experienced who took part in the survey. As 36.9% had experience of 2-5 years, and other 26.3% had experience of less than 2 years and remaining 25% were having experiences of 6-10 years and 11.9% had experience of more than 10 years.

**Table 2: Type of Organization**

Type of organization					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Public Sector	59	36.9	36.9	36.9
	Private Sector	69	43.1	43.1	80.0
	Nonprofit Organization	32	20.0	20.0	100.0
	<b>Total</b>	<b>160</b>	<b>100.0</b>	<b>100.0</b>	

The respondents were employees in a mix of private, public and nonprofit organizations, which provides insight on the degree of AI integration, and the key differences in attitude towards the use of technological innovations in the recruitment process. As shown in the above Table (3), data results depicted that the respondents were from three different sectors. 36.9% were from the public sector, 43.1% were from the private sector and remaining 20% were from the non-profit organizations.

**Table 3: Size of Organization**

Size of organization					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Small (1–50 employees)	51	31.9	31.9	31.9
	Medium (51–250 employees)	73	45.6	45.6	77.5
	Large (250+ employees)	35	21.9	21.9	99.4
	<b>Total</b>	<b>160</b>	<b>100.0</b>	<b>100.0</b>	

To understand the volume of recruitment activities in the organization and the role that AI could potentially or is being applied, the size of the organization is another factor considered. In the total number of respondents who took part in the survey, 31.9% were employed in small sized organizations, while 45.6% were employed in medium sized organizations and remaining 21.9% were employed in larger sized organizations.

## Inferential Analysis and Hypotheses Testing

Inferential analysis provides a clear understanding in the relationship found between the independent variable, mediating variable and dependent variable. This section conducts correlation and regression tests to identify the relationship between variables, which would either result in a positive or negative figure, indicating the direction of the correlation.

### Correlation

The Pearson correlation analysis test is chosen to determine the strength of the relationship between the variables. The values of the correlation coefficient vary between -1 and +1. Values close to +1 are considered to have a strong positive correlation with each other, while those closer to -1 are considered to have a strong negative relationship with each other. The variables valued 0 are considered to have no relationship with each other.

**Table 5: Results of Pearson Correlation Test**

Variables	AIS	SE	UES
AIS	1.00		
SE	0.816	1.00	
UES	0.957	0.782	1.00

\* All correlations are statistically significant at  $p < 0.05$ .

Pearson correlation test results in Table (7) reveals strong positive correlation among all variables. AIS and SE showed high correlation at ( $r = 0.816$ ). The table also showed an extremely strong positive correlation between AI-based Staffing and Unbiased and Ethical Selection, with a score of ( $r = 0.957$ ). Moreover, UES was strongly correlated with SE at ( $r = 0.782$ ); thus, suggesting that Unbiased and Ethical Selection functions as a mediator in the relationship between AI-based Staffing and Staffing Efficiency.

### Regression

For regression testing, the linear regression model was applied three times for testing all three hypotheses consecutively.

#### ***H1: AI-Based Staffing Significantly Impacts Unbiased and Ethical Selection***

This hypothesis is based on the idea that AI-Based Staffing has a direct impact on the extent of fairness and ethical behavior during the process of choosing candidates. The test is conducted to identify whether AI significantly minimizes human bias and enhances more objective and transparent decision-making in the selection process.

**Table 6: Model Summary**

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.757 <sup>a</sup>	.717	.716	.24784

a. Predictors: (Constant), AI-Based Staffing

According to the regression model presented in Table (6), the value of 0.717 means a regression model of 71.7%, which has a high predictive level to provide accurate and effective results.

Results for hypothesis 1 showed a P-value of 0.00 (significance constant), which is less than the threshold value of the constant (0.005). This shows a direct impact of the changes in the independent variable on the value of dependent variable. The result indicates that usage of AI-Based Staffing can significantly affect Unbiased and Ethical Selection within the organization, which means hypothesis 1 can be accepted.

**Table 7: Coefficient**

Coefficients <sup>a</sup>						
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	.213	.054		3.931	.000
	AI-Based Staffing	.889	.021	.957	41.668	.000

a. Dependent Variable: Unbiased and Ethical Selection

Table (7) illustrates the value of the coefficient constant (Beta value) of the regression model was 0.957, which was quite high, verifying significant and highly dependent relationship between AI-Based Staffing and Unbiased and Ethical Selection.

***H<sub>2</sub>: AI-Based Staffing significantly impacts Staffing Efficiency***

According to this hypothesis, AI-Based Staffing is important in enhancing the general efficiency of Staffing, including speed, consistency, and accuracy in personnel recruitment operations. The test is taken to check whether AI-driven tools indeed lead to the ease and effectiveness of staffing processes in organizations.

**Table 8: Model Summary**

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.816 <sup>a</sup>	.667	.664	.51527

a. Predictors: (Constant), AI-Based Staffing

The regression model summary in this research showed that the value of R-square of this model was 0.664, which showed that the model can predict the value of regression with 66.4% accuracy, which was on the higher side. It can be considered that regression model can predict the relationship between the variables accurately.

Regression test result for hypothesis 2 revealed that a P-value (significance constant) is 0.000, which is below the standard P-value of 0.005. This predicts that there is a direct relationship between the independent variable (AI-based Staffing) and the dependent variable (Staffing Efficiency). Therefore, it can be predicted that the usage of AI-based Staffing practices can enhance overall staffing efficiency within the organization, which confirms hypothesis 2.

**Table 9: Coefficient**

Coefficients <sup>a</sup>						
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	.487	.113		4.323	.000
	AI-Based Staffing	.788	.044	.816	17.771	.000

a. Dependent Variable: Staffing Efficiency

The above presented coefficient Table (9) presented that the beta value of 0.816, which showed that the degree of the impact of the independent variable on the dependent one was strong, but not as much significance as it was in the case of the first hypothesis.

***H3: Unbiased and Ethical Selection mediates the relationship between AI-Based Staffing and Staffing Efficiency***

According to this hypothesis, Staffing Efficiency is a mediating factor between AI-Based Staffing and Unbiased and Ethical Selection. The test seeks to determine whether a positive effect of AI on ethical decision making is indirectly determined by efficiencies in the staffing processes.

**Table 10: Model Summary**

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.816 <sup>a</sup>	.667	.662	.51690

a. Predictors: (Constant), Unbiased and Ethical Selection, AI-Based Staffing

The above-mentioned regression model summary depicted that value of adjusted R-Square was 0.662, which indicated that this regression model could predict the relationship between variables with 66.2% accuracy.

Further, hypothesis 3 depicts the significance value (P-value) of 0.992, which is higher than the threshold P-value of 0.005. This value shows that the regression outcomes are not statistically significant and that the relationship between AI-Based Staffing and Staffing Efficiency is not mediated by Unbiased and Ethical Selection in the organization. Thus, hypothesis 3 is not accepted in this analysis.

**Table 11: Coefficient**

Coefficients <sup>a</sup>						
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	.486	.118		4.110	.000
	AI-Based Staffing	.787	.154	.815	5.107	.000
	Unbiased and Ethical Selection	.002	.166	.002	.010	.992

a. Dependent Variable: Staffing Efficiency

Table (11) indicates that AI-Based Staffing has a beta of (0.815), which suggests that this variable highly and positively correlates with Staffing Efficiency. But the beta of Unbiased and Ethical Selection was (0.002) and non-significant p-value, which means that this variable does not contribute to the model and does not mediate the relationship between AI-Based Staffing and Staffing Efficiency.

**Table 12: Summary of Findings**

Hypothesis	$\beta$ -value	P-value	Remark
H1	0.957	0.000	Accepted
H2	0.816	0.000	Accepted
H3	0.002	0.992	Rejected

The results show that two among the three hypotheses were accepted. Hypothesis 1 exhibited the greatest effect where AI-Based Staffing was found to have very significant and positive effect on Unbiased and Ethical Selection. This indicates that the implementation of AI in staffing can elevate equity, transparency, and morality in the process of selection.

Likewise, Hypothesis 2 was accepted and showed a significant positive correlation between AI-Based Staffing and Staffing Efficiency. This implies that AI application helps in enhancing efficiency, speed, and accuracy in staffing processes in the organization.

Nevertheless, Hypothesis 3 was rejected. Whereas AI-Based Staffing was still a significant predictor of Staffing Efficiency, Unbiased and Ethical Selection did not play a significant role when added as a mediator. The absence of a mediating effect is confirmed by the very low value of beta ( $\beta = 0.002$ ) and the high value of p-value (0.992). Thus, Staffing Efficiency improvements seem to be a direct outcome of AI-Based Staffing, and not as a result of ethical or unbiased selection practices. In general, the findings indicate that AI-Based Staffing has a powerful direct influence on ethical selection outcomes and staffing efficiency, but the mediating role of Unbiased and Ethical Selection was not confirmed in the research.

## Discussion

The results of the data analysis provided strong and statistically significant illustrations of all three research hypotheses that formed an image of a clear but complex picture of the role played by AI in modern staffing processes. Hypothesis 1 (H1) about the perception that AI-based staffing has a strong direct influence on the creation of an unbiased and ethical selection is confirmed with a resounding positive, as an exceptionally high beta value ( $= 0.957$ ). Such a strong correlation indicates that in the companies that partake in the survey, the adoption of AI tools is closely related to the transition toward a more procedurally just, transparent, and objective approach to the evaluation of the candidates.

This observation makes AI not only a tool of efficiency, but also a possible foundation of ethical HR governance, which would directly respond to the issue statement worry around unequal and unfair human decision-making. The positive correlation between Hypothesis 2 (H2) and operational argument is strongly supported by the fact that the correlation is positive ( $0.816$ ) and proves the essential argument of AI adoption. It is an empirical finding that AI tools can

significantly transform the labour-intensive processes of screening resumes and preliminary filtering of candidates, and, thus, make the recruitment lifecycle time a critical performance indicator that will be measured during the survey. This is twice efficient: it makes the administrative function less expensive and, according to the replies, it frees the recruiters to do more strategic and value-added work, such as candidate relationship management and in-depth interviewing.

This outcome is a direct operationalization of the principles of staffing efficiency described by Rathore (2023) and it shows that the theoretical benefits of AI are already being realized in practice and making the recruitment process more agile and responsive. Nonetheless, the most subtle and least statistically meaningful result pertains to Hypothesis 3 (H3), which assumed Unbiased and Ethical Selection to be a mediating variable between AI-Based Staffing and Staffing Efficiency. This mediating relationship was not supported by the empirical analysis, meaning the relationship between AI adoption and enhanced efficiency is not mediated by the perceptions of fairness or ethicality.

This finding indicates that the effects of AI technologies on efficiency do exist even without ethical or unbiased selection. Although ethical AI is an urgent organizational concern especially in the process of reducing risks related to biased decision-making, legal liability, and negative publicity, it can be concluded that the current findings show that it is not the mechanism that enabled the achievement of efficiency gains in the current case. Thus, despite the ultimate necessity of fairness as a condition of long-term sustainability and accountable HR governance, it did not mediate statistically between AI-Based Staffing and the efficiency of staffing in this framework.

The lack of a mediating effect provides a valuable explanatory message, that ethical AI is not an ethical supplement, but is central to the long-term, sustainability of staffing efficiency. These findings are further enhanced by the demographic profile of the respondents, which provides an external validity. The presence of the HR professionals representing the mix of the public, private and non-profit, and the small, medium, and large enterprises implies that these relations are not bound to a particular industry or the size of an organization. This diversity indicates that AI has a wide-ranging effect on staffing, applicable to the rest of the economic environment. The diversity of experience within the respondents, including both beginners and experienced veterans, also supports the data, as it suggests a vast area of beliefs on the merging of technology with old practices in HR.

Finally, the reliability tests have shown high internal consistency in all the constructs which assert that the survey instrument remained coherent and had the ability to give reliable data that could be further analyzed. The fact that the regression and correlation findings are consistent provides an additional point of strength to the findings in relation to each of the hypotheses, which in conjunction, provides a substantial and believable baseline to interpret the relationship between AI-Based Staffing, Staffing Efficiency, and Unbiased and Ethical Selection. This statistical rigour adds credibility to the validity of the conclusions made and makes sure that the observed patterns are based on consistent data.

A significant proviso that accompanies this finding is the extremely high Beta value ( $\beta = 0.957$ ) for the correlation between AI-Based Staffing and Unbiased and Ethical Selection, which may be due to perceptual alignment, rather than algorithmic actuality. HR professionals think AI is fair, and they want it to be fair, which is a cognitive bias that justifies investing in AI automation and accepts that human oversight is being minimized. This perception gap is not insignificant; the same respondents who agree strongly that AI improves fairness might not be aware of the algorithmic biases that may exist, or the fact that the data used to train AI is potentially flawed, or that the steps involved in decision making are opaque. The result in H1 is thus accepted as statistically significant, but the size of the effect should be taken as a measure of the belief in ethical AI, not the proven, audited fairness.

## **CONCLUSION AND RECOMMENDATIONS**

### **Conclusion**

This study evaluated how AI impacts staffing activities with the main focus on candidate selection efficiency, fairness and ethical considerations. There are three objectives of this study which include investigating how AI improves candidate selection efficiency, to evaluate the fairness and ethical concerns aligned with AI-based staffing to explore the mediating role of unbiased and ethical selection between AI use and staffing efficiency. Furthermore, this study employed a quantitative methodology and the data for this study collected from 160 HR professionals as it offered valuable insights into the practical use of AI in recruitment.

Additionally, findings from the literature review and data analysis highlighted that AI has become an important tool for the modern recruitment system. The AI system supports the HR professionals by mitigating the time needed for screening resumes, automating repetitive tasks and offers data driven insights for decision making. The respondents from the study agreed that AI tools helps in streamlining the recruitment cycle, mitigates the manual workload and enhances the overall speed of candidate selection. These findings from this study support previous studies that focuses on the ability of AI to enhance efficiency and accuracy.

However, this study also indicate that the advantages of AI also include various challenges as main concern includes fairness and bias. Various studies mainly indicates that AI mitigates the human bias but recent researchers indicate that AI system can develop an unintentional and systematic bias because of flawed data inputs, coding choices or algorithm design. The result of survey highlighted same as many participants agreed that AI contributed to increased fairness and transparency while others believed that AI should never operate without clear human oversight, strong ethical guidelines and accountability mechanisms.

According to the results of the current study, Unbiased and Ethical Selection is not the mediator between AI-Based Staffing and Staffing Efficiency. Rather, the efficiency gains that come along with AI are directly related to its functional capabilities, and not by ethical or unbiased selection processes. This supports the fact that AI systems do not provide fairness per se, rather fairness arises when organizations consciously incorporate ethical principles, transparency, and human control in the recruitment procedures. In this context, respondents took part in this study

highlighted the significance of informing candidates when AI is used and ensures adherence to the data protection standards.

Overall, this study highlighted that AI improves staffing efficiency but, in the case, when supported by ethical guidelines. Furthermore, AI can mitigate time, increase accuracy and assist HR professionals in making better decisions. However, over dependency on the automated system can lead to organizations to risks that include algorithm bias, lack of transparency and mitigated trust among the applicants. So, a balanced approach which blends AI capabilities with the human judgement was viewed as most effective and ethical method for recruitment.

Comprehensively, this study contributes towards existing knowledge by indicating that AI should not be perceived as a replacement for human recruiters but instead as a complimentary tool. The HR professionals must continue to play a key role to make sure that candidate selection remains fair, inclusive and aligned with organizational value. In addition to this, ethical frameworks, training and ongoing analysis are very important to increase the positive impact of AI on staffing.

### **Recommendations**

On the basis of the findings from this study, the following recommendations are proposed for company's HR professionals and policy makers who focuses on using AI responsibly in recruitment process. The companies should develop clear and detailed ethical guidelines for the use of AI in staffing which include how candidate data is gathered, stored and protected, the level of human oversight needed in decision making, process for determining and addressing the algorithmic bias, and clear communication policies which informs candidates about involvement of AI. Such guidelines enhance the transparency and help in building trust among the applicants. Additionally, the ethical guidelines also make sure that AI tools adhere to the legal requirements that consists data protection laws and equal opportunity regulation.

In addition to ethical guidelines, study recommends that the AI alone cannot guarantee unbiased and fair recruitment so the HR professionals should review the AI-generated suggestions and always make final hiring decisions by themselves. The human oversight in recruitment process can help in determining the errors in AI-generated shortlist, helps in detecting biased patterns in automated screening, and analyze soft skills or contextual details that AI may miss or ignore. By implementing these insights, organizations can get advantages of speed of AI along with ensuring fairness and accountability.

Furthermore, the HR teams must get training to gain insights into how AI tools work which include their limitations too. The training should include recognizing various types of algorithm biases, interpreting AI generated data and results, ethical and legal responsibilities at the time of recruitment, and technical skills to monitor and adjust the AI system. The well-trained HR professionals are better skilled to use the AI responsibility and make sure that staffing outcomes remain fair.

Moreover, the company should test the AI system periodically and should be audited to make sure that they do not develop biased results. This Recommendation can be implemented through examining patterns of candidate rejection, the accuracy of AI-generated rankings, adherence to the fairness and non-discrimination standards, and the influence of data quality on AI decisions. The

regular audits help the companies in determining problems proactively and mitigate reputational ethical and legal risks.

Lastly, companies should use high quality and diverse training data, enhance transparency with candidates, embrace a hybrid recruitment model and develop guidelines for ethical use of AI in hiring. As by using high quality and diverse training data helps the company in mitigating the risk of discriminatory recommendations and enhances the accuracy of AI. Furthermore, improving transparency with the candidates can further enhance trust and enables the applicants to gain insights into the process. Moreover, by adopting hybrid system, the HR professionals can emphasize on strategic roles along with maintaining strong ethical control on the recruitment decisions. Finally, clear policy direction will help in embracing AI responsibly across industries and also helps in protecting the rights of candidates.

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