Algorithmic Fairness in Recruitment: Designing AI-Powered Hiring Tools to Identify and Reduce Biases in Candidate Selection

Chinyere Linda Agbasiere [1], **Goodness Rex Nze-Igwe** [2]

[1] *Illinois State University*
100 N University St, Normal, IL 61761, USA

[2] *University of Louisville*
2301 South 3rd Street, Louisville, KY 40292, USA

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Corresponding Author:
Chinyere Linda Agbasiere
agbasierechinyere@gmail.com

Abstract. The study looks into how Artificial Intelligence (AI) affects hiring procedures, focusing on the fairness of the algorithms that drive these tools. AI has improved the efficiency of the hiring process, yet its use results in institutionalised discrimination. The AI systems used for recruitment, which base evaluations on past performance data, have the potential to discriminate against minority candidates as well as women through unintentional actions. The ability of AI systems to decrease human biases during recruitment encounters presents major challenges, as Amazon's discriminatory resume screening demonstrates the issues in systemic bias maintenance. This paper discusses the origins of algorithmic bias, including biased training records, defining labels, and choosing features, and suggests debiasing methods. Methods such as reweighting, adversarial debiasing, and fairness-aware algorithms are assessed for suitability in developing unbiased AI hiring systems. A quantitative approach is used in the research, web-scraping data from extensive secondary sources to assess these biases and their mitigation measures. A Fair Machine Learning (FML) theoretical framework is utilised, which introduces fairness constraints into machine learning models so that hiring models do not perpetuate present discrimination. The ethical, legal, and organisational ramifications of using AI for recruitment are further examined under GDPR and Equal Employment Opportunity law provisions. By investigating HR practitioners' experiences and AI-based recruitment data, the study aims to develop guidelines for designing open, accountable, and equitable AI-based hiring processes. The findings emphasise the value of human oversight and the necessity of regular audits to guarantee equity in AI hiring software and, consequently, encourage diversity and equal opportunity during employment.

Keywords: AI recruitment; algorithmic-based fairness; Bias mitigation; human resources; artificial Intelligence; Equal Employment Opportunity.

INTRODUCTION

Algorithmic fairness, when employed, aims to create AI-powered recruitment software that spots and cuts down on bias when selecting job candidates. This enhances the recruiting process's inclusivity and equity by evaluating all applicants on the same standards, focusing on job-related abilities and qualifications regardless of demographic traits such as gender, race, or ethnicity. We live in an era where technology impacts industries and business operations [10]. AI has emerged as one of the most significant trends in the field of recruitment [4, 17, 39, 73, 97]. Because the technology can make decisions and assimilate information at levels and rates much beyond human capability, it improves efficiency in spotting, hiring, vetting, assessing, interviewing, and supervising employees [70]. AI recruitment and selection software is not without fault.

Nevertheless, it can reflect and perpetuate diversity bias, thus discriminating against job candidates based on their traits [27, 36]. A good example is The Amazon resume selection algorithms, which were based on past gender disparities in the firm's hiring, with men over women for technical positions [59]. Even though the Amazon resume screening algorithm was never made public, it exemplifies the profoundly negative effects of training algorithms with insufficient diversity and inclusion. If unguarded in its application, the possible effect on the dignity, independence, and welfare of a job candidate reaches into many aspects of their lives, including them but not limited to social interaction, financial standing, housing prospects, domestic life, and possible influence on physical and mental well-being. Therefore, to continue to benefit from technological innovation, HR professionals and employers must be able to manage the risks involved and determine whether using such technologies can have minor negative effects. Therefore, companies and HR professionals must ensure that their AI solutions for recruiting are equitable [100]. Artificial Intelligence (AI) aims to improve hiring practices through large-scale operations, organisational-wide efficiency gains, and data-based selection capabilities, which have completely changed the recruitment process [18]. AI technology scans resumes and candidate evaluations and performs initial interview screening functions that help organisations during recruitment. Critics have pointed out that algorithmic bias exists within AI hiring systems because it unintentionally makes historical hiring data biases stronger and more prevalent [74]. The success of an organisation depends heavily on recruitment since it determines which qualified candidates get chosen while shaping both performance levels and cultural dynamics. The standard recruitment system is based on job advertisements and performance and personality evaluation tests. Studies [78] conducted were carefully reviewed by industrial-organisational (I-O) psychologists and human resource (HR) specialists. Research indicators validate how these assessment procedures affect multiple organisational dimensions related to performance levels, employee retention, and workplace productivity [16, 53]. The outcomes from these recruitment practices influence substantial numbers of job-seeking candidates annually because workers generally stay in their roles for 4.2 years before transitioning to new employment opportunities, 12.3 times during their professional careers [103]. Modern organisations implement inventive hiring methods to enhance their long-term performance while improving their workforce selection procedure.

Digital recruiting 1.0 emerged in the 1990s, and it contained online job criteria and the option for candidates to send credentials automatically. Digital recruiting has evolved the hiring process substantially during the last three decades, with a steady transition towards an electronic recruiting system. The development of digital recruitment proceeded through three separate phases [17]. The internet recruiting market began to be dominated by job board websites such as Indeed and Monster following the beginning of the century [17]. Job seekers could find suitable positions through search and recommendation tools on platforms that combine job postings from multiple organisations [17]. In the modern Internet recruiting 3.0 age, artificial Intelligence has transformed hiring practices across job boards, online networking sites, and HR platforms [17]. Companies use AI for various business tasks, including creating job ads, implementing applicant tracking systems, conducting phone and video interviews, and creating gratified tests [17, 78, 106].

Criteria for constructing impartial AI recruiting mechanisms. To ensure impartial and equitable hiring of AI talent, it is necessary to design unbiased recruitment tools. Initially, it is essential to incorporate a variety of training data. The Artificial intelligence system can learn from candidates' profiles from different backgrounds without being subjected to biased demographic patterns. To spot and fix potential bias, it's crucial to keep checking and watching for it all the time. This means doing regular reviews and looking at candidate data across different groups. Ensuring people can see how the AI makes decisions helps make things fairer. It gives everyone involved a clear picture of how candidate scores are worked out, making finding and fixing biases easier. The people who design the system's features need to pick job-related traits. They should leave out names, addresses, and where someone went to school to avoid unintended bias. Incorporating human oversight into the recruiting process allows recruiters to evaluate applicants using an AI-generated ranking and utilise the findings to ensure objectivity. Several factors have been recently studied to increase the equity of AI-based hiring. As authors set forth, an organisation's recruitment process is pivotal to its ability to place itself advantageously in the labour market by determining qualified and suitably matched persons, thereby shaping its output and organisational culture. Accordingly, in the last century, human resource practitioners and industrial-organisational psychologists have developed work practices entailing the targeting of potential applicants through job ads, assessing applicant ability, and applying questionnaires to establish organisational fit. However, the arrival of big data and machine learning has rapidly altered the traditional recruitment process, with most firms now using artificial Intelligence.

Artificial intelligence-driven recruiting is becoming the norm. It is more and more of a worry that human biases can influence decision-making by such a system and can also be perpetuated through systematic enforcement. The past decade has been filled with studies on AI fairness in evidence of widespread prejudice in candidate-ranking systems and chats between bots. Decision algorithms have been widely used in society in large numbers, whose transparency is in question, along with a threat of being used as new discriminatory weapons. The consensus is on human-centric style systems of artificial Intelligence. Four requirements drive human-centric learning: a perception of utility and public utility, data ownership and privacy, transparency and responsibility (ii), and fairness in AI decisions. The four requirements go hand in hand with human-centric. We make a case study on automated hiring based on a flawed assumption in which multimodal algorithms based on different data sources have been polluted by internal prejudice and complicated factors.

How can AI be leveraged to mitigate bias in the workplace? Artificial Intelligence (AI) improves hiring by standardising employee assessments, which lessens the subjective biases of human recruiters who can selectively evaluate candidates' abilities and experiences through blind screening, which eliminates any personal information related to names or locations. Also, AI examines job descriptions to identify and correct language that may discourage different applicants. Why? It also reveals candidate preferences and areas that require better outreach, offering insights into the diversity of candidates. Algorithms' fairness is a difficult task. AI models' performance relies on reliable, representative training data that can be challenging to obtain, particularly for various candidate groups. Aside from that, societal biases can inadvertently shape AI systems even with careful design. It is difficult in a normal scenario to detect and neutralise biases in AI driven by complex decision-making, which is difficult to explain. It is thus essential to develop and deploy AI-based hiring tools with fair dealing in mind and the vision of promoting inclusive hiring.

Research Problem. The potential of AI for recruitment is significant, but algorithmic bias remains a major obstacle. The historical hiring data in AI models may include biases against gender, race, and socioeconomic groups [12]. However, this data is non-existent in the system. When poorly constructed, AI can lead to biased hiring based on a preference for marginalised group job applicants. Current methods of reducing bias in AI hiring are narrow and patchy. Many entities have none of these systems to ensure fairness, transparency, and accountability in AI hiring.

Additionally, regulating measures such as the GDPR or EAO highlight an imperative to establish fair hiring practices based on AI, but there is no clear enforcement mechanism [87]. This study investigates the discrepancy between AI effectiveness and fairness in recruiting. A discussion on developing, evaluating and improving hiring tools that use AI. To minimise discrimination and promote fairness in the preference for candidates.

Research Questions

How do AI-powered hiring tools contribute to or mitigate biases in candidate selection?

What strategies and frameworks can be implemented to ensure algorithmic fairness in recruitment?

What are the moral, legal, and organisational ramifications of employing AI in recruitment?

Aims & Objectives

To analyse how biases manifest in AI-powered hiring tools and their impact on fairness in recruitment.

To evaluate different algorithmic fairness techniques (e.g., reweighting, adversarial debiasing, and fairness-aware algorithms) and their effectiveness in reducing bias.

To explore the ethical, legal, and organisational considerations involved in designing and implementing fair AI recruitment systems

Scope of Study. This research examines AI-driven hiring tools to detect and mitigate selection biases in candidate evaluation. This study scrutinises how bias detection methods, such as adversarial debiasing and reweighting, along with newer fairness-aware algorithms, serve as tools to enhance the identification of gender, race, and socioeconomic discrimination. The study scrutinises the ethical, legal, and organisational implications of GDPR and Equal Employment Opportunity regulations using AI recruitment data and HR professionals' experiences. This research seeks to establish guidelines for developing impartial AI recruitment mechanisms, guaranteeing openness, accountability and adherence to fairness regulations.

Justification of the research. Since Artificial Intelligence is successful in many HR tasks, its application in hiring is growing. Why? Digital screening is crucial in one way because it expedites the hiring process and may lessen human prejudice. Automated recruitment processes have become increasingly vital for large organisations managing hundreds or thousands of programs [17, 43]. AI uses large language models (LLMS), such as Chatgpt, to generate job postings, which helps draw in the best applicants [82].

Additionally, LLMS are used to improve contact with job applicants and create interview questions. A considerable rise in the usage of AI in hiring and recruitment is anticipated due to the trend towards remote labour, especially in the wake of the COVID-19 pandemic [42, 91]. According to recent figures, 88% of firms worldwide used artificial Intelligence in some capacity as of 2019, underscoring the importance of AI's involvement in hiring. In particular, 41% of respondents said they communicated with candidates using AI-powered chatbots, 44% said they recruited using social media and other publicly accessible data, and 43% suggested AI training [20]. Access to cloud storage and processing power has seen AI being adopted in the recruitment process, which is most likely to grow. However, as AI becomes more prevalent, there are concerns that decision-making by these systems may be biased against organisational personnel or model developers, according to recent reports [78]. Women were more likely to view high-income job postings on Google's job recommendation system 2015 [76]. Because of gender bias, the discriminatory practice of Amazon's AI-based candidate evaluation tool led to its discontinuation in 2017 because of the low representation of female candidates in the model's training data. This feature has likewise been removed from the company's platform.

Furthermore, Facebook faced similar issues in 2019 with its housing and job delivery systems, with job advertisements discriminating against users based on race and gender [8]. Employment biases frequently present in the employment process can be easily transferred when data is used to train algorithms in AI-based systems. These are illustrative cases.

Outline Methodology. This study gathers data from extensive secondary sources using a quantitative approach. It examines job searchers' and HR professionals' experiences to determine their interest in AI hiring. Algorithm bias will be identified using fairness metrics like equalised odds and differential impact analysis. A study will compare methods of reducing bias, such as reweighting and adversarial debiasing. Statistical analysis will be limited to SPSS, replacing the Python-based fairness assessment tools. With an emphasis on enhancing comprehension of these concerns, the research uses structured data analysis to evaluate biases and reduce potential dangers related to AI-based hiring.

Literature Review

AI integration has transformed traditional hiring processes, boosting recruitment efficiency and scalability while enhancing decision-making capabilities. AI-driven recruitment systems manage the processes of job advertisement publication, candidate screening, and interview assessment. The issue of algorithmic bias remains problematic because AI models incorporating historical hiring data potentially perpetuate discrimination against underrepresented groups. This chapter critically analyses a comprehensive literature review regarding AI recruitment systems alongside studies on algorithmic fairness and methods to counteract bias. The paper looks at how AI can help and hinder fair hiring practices, its uses' moral and legal ramifications, and the suggested frameworks for ensuring accountability, transparency, and equity in AI recruiting processes.

The employment and selection procedure now utilises artificial intelligence applications. Human beings performed selection and recruitment activities until the late 1990s. HR professionals conducted recruitment by hand before screening job applications and evaluating candidates to determine which people could advance in the hiring process for potential employment. As shown by human resource specialists, conventional recruiting methods have proved to be laborious and prone to unintended and intentional biases [11, 17, 24]. This implies that hiring professionals have the tendency to stereotype and discriminate against job applications intentionally or unknowingly based on their traits, including gender and age. However, in the 1990s, the advent and rapid growth of the Internet transformed the hiring process. Online job boards emerged as one change that compiled numerous job listings to draw in numerous job seekers through an efficient and cost-effective method [15]. Through the network effect, websites with greater job inventory attracted larger candidate volumes, which increased company participation in paid services. Online recruiting, also known as e-recruitment, took the form of professional networking websites simultaneously. This allowed people to create and expand a network based on similarities in their jobs, making it easier to share recommendations and information [11, 17] – websites like Monster, Indeed, Glassdoor, LinkedIn, and many more. Scholars [57, 94] provide ample evidence for this claim. LinkedIn's highly skilled candidate pool drove more organisations to utilise the platform, making it grow quickly and developing more advanced AI innovations. To date, HR practitioners work in a continuously changing environment, frequently struggling to keep pace with technological progress [40]. The decisive power of artificial Intelligence in talent acquisition has become increasingly clear to organisations searching for AI-based recruitment and selection methods [6, 57, 94].

The goals of AI-powered hiring and selection. The transition consists of business recruitment modifications integrating AI applications to handle essential recruitment functions, including outreach and screening before assessment and coordination [27, 47]. AI applications leverage different posting channels to reach maximum audience response through banners, pop-ups, emails, and text messages that offer capabilities similar to digital marketing initiatives. HR practitioners can utilise AI to improve their recruitment efforts [54]. The capabilities of artificial intelligence tools surpass those of human recruiters when screening job candidates since these tools both speed up processes and analyse digital footprints for specified abilities and personality traits from social media data [51]. Machine learning tools support stage coordination among recruitment stages and help Human Resources professionals through the assessment phase (especially when using gamification) [45, 81]. The decisions in this recruitment process create evaluative data points that produce feedback throughout successive steps. AI-based screening and outreach applications will need job tenure prediction as an essential goal to influence future employment retention based on assessment results – Hacker [40]. The increase in human resources management automation levels does not eliminate the need for human intervention following AI tool developments that aim to replace or automate HR professionals. The current automation practice exists in the board of directors' management, civil aviation control, and surgical procedures [37]. Humans retain their unmatched role in all work processes. The responsibility of HR managers lies in technological execution to achieve preset performance standards, where machines handle recruiting and candidate selection functions [86]. The text declares that AI applications do not display the emotional abilities, intuitive capabilities, or content-sensitive skills humans naturally hold to perform tasks efficiently [33]. The design phase of technology requires continuous human supervision since people determine both its creation and data selection, and they oversee testing and training operations [37, 45]. Generally, any organisation's ability to survive and succeed closely correlates with its ability to recruit and choose the best candidates.

In other words, the hiring process produces a workforce with the perfect combination of talents, abilities, knowledge, and other characteristics required for a competitive edge [2, 60]. Organisations utilise AI technology for recruiting and selection to gain a competitive edge in the talent competition [34]. In general, it is anticipated that AI applications will contribute to improving time, cost, and effort efficiency in almost every recruitment and selection process [45, 50, 96]. Since hiring may be a fairly drawn-out process involving extensive job ads, many rounds of interviews, and complex decision-making processes frequently constrained by geographic boundaries, time, and location, these are typically important restraints in the traditional hiring paradigm. Organisations may easily access a worldwide talent pool of candidates without being constrained by physical geography, thanks to AI-driven solutions that enable them to overcome the limitations imposed by geographic location. Traditional hiring limitations vanish when AI tools are implemented, enabling more hiring process flexibility [65] and significantly expediting this procedure by automating certain hiring-related tasks. For example, automatic screening technology analyses abundant candidate pools much faster than human recruiters do to identify prime candidates. Virtual assistants and chatbots maintain interaction availability for all candidates through day and night business hours to support their flexible assessment needs [9]. AI-driven solutions help minimise administrative tasks for interview scheduling and coordination since companies often dislike these tasks during hiring [56]. Employers and candidates may find the process more responsive and efficient if these procedures are automated.

HR professionals should balance their creative and intuitive decision-making capacity with AI's analytics capabilities for managing intricate and substantial data sets [55]. Predictive analytics combined with machine learning models allow organisations to forecast employee requirements, thus maintaining continuous staffing by discovering talent before positions become available [9, 46]. Additionally, AI applications appear to be quite good at identifying the most important (and frequently less obvious) factors that affect how well job candidates match open positions [60]. Lastly, some academics believe that AI-powered programs offer greater impartiality and make less personal decisions because they seem to handle recruitment and selection activities with little direct human participation [50].

Recruitment Tools with Algorithmic Bias. Algorithmic bias occurs when AI hiring technologies reflect and amplify human prejudices in training data [12]. It has been demonstrated that racial and gender biases are more common in AI hiring algorithms. Research showed Amazon discarded its AI recruiting system because it repeatedly selected male candidates over women [32]. Biased feature selection, inadequate model training, and data imbalances can all lead to bias [19].

Reasons behind Bias. A variety of regular paths allow human prejudice to enter AI models.

Biased training data will cause an AI system trained in this fashion to retain and distribute bias during operation. Using human labels can introduce preexisting human bias to the labelling process, which results in dirty label effects. In contrast, biased samples occur when one group appears more frequently than others in the outcome.

Definitions of labels: In machine learning, a model's target label is what it hopes to predict. The disparate impact may increase if the intended outcome is defined in an integrated or ambiguous manner. A manager can utilise multiple definitions to enhance hiring success by developing a classification model that predicts job candidate quality [12]. Employees' motivation primarily determines a candidate's suitability for a business and their work performance expectations, the job-person fit between applicants and available roles, and the person-environment fit between job seekers and business culture and environment [14, 64]. Overgeneralised labels for protected groups throughout historical employment data will produce abnormal model forecast results. Employers should avoid targeting women's expected job durations with tenure predictions since historical data reveals shorter stays by women in their roles. This approach potentially creates biased views against female candidates [12].

Feature selection describes traits that assist AI models during prediction tasks in determining outcomes from given feature data. Feature selection models improve accuracy by decreasing data complexity while shortening the learning period [101]. How statistical variations appear within protected classes for any particular feature leads to bias in the data analysis. Classifying protected categories requires features that might be excessively simple for an AI system to learn proper identifications. AI systems often mistake capable job candidates from protected classes as unqualified when the protected members have an abnormal college graduation rate. Hiring processes commonly use college education information as well as enrolled institutions.

Proxies: Even if the protected attributes were eliminated from the training data, other attributes might still be used to establish group membership, potentially leading to biased selection. For example, the model may use the applicant's school on their resume to determine gender (all-male or all-female schools). Except for the gender feature, the application displayed bias during recruitment [75].

Masking: When designing features or gathering data samples, employers or model developers with prejudicial preconceptions may purposefully influence the AI model by breaking predictive parity [12]. To make an AI model bias against particular protected groups appear acceptable, masking is a technique that uses data representation (for example, only employing coarse-grained model characteristics that hide fine-grained group information).

AI-Based Recruitment Bias. According to HR and I-O psychology research, the hiring process consists of four stages, as presented below [49]. The subsequent analysis section details AI-based assessment methods and their implicit biases and bias reduction strategies present at each hiring phase.

The employer seeks available positions at their firm to specify essential requirements, such as experience and KSAOs that qualify applicants for positions. Employers implement the first step when starting their hiring process. The step requires organisations to evaluate what factors lead to proper person-environmental integration [93]. The process determines whether personal traits and values align effectively with organisational work culture standards. The workplace begins candidate sourcing by following job analysis to attract potential candidates, from which they create a pool. This is accomplished through employee referrals, recruiter outreach, and the creation of job ads that reflect the defined KSAOs. These include AI-based solutions for candidate sourcing and job analysis, and AI-powered systems for finding candidates, like HireEZ. Hiretual communicates with a wider range of candidates by utilising AI.

Furthermore, LLMs are employed for several purposes, including creating job advertisements. Prompting-based interfaces such as TalentGPT are used to source talent and perform job analyses. SeekOut, BrightHire, and Textio are further AI services that are also offered to make finding candidates easier.

1) Candidate Screening. The second recruitment phase, candidate screening (candidate matching), is where a preliminary set of candidate profiles, i.e., resumes, is screened based on person-job fit. In the process, ranking and screening tools are typically used by large companies handling thousands of resumes. Among the AI-powered screening techniques are those offered by SeekOut. They provide personality tests, methods for rating and filtering resumes, and assessments of candidates' work experience and knowledge [26, 107]. However, like other AI applications, screening models can also be biased, as previous applications, such as Amazon's resume sorting tool, demonstrated. Due to the training set's reliance on past hiring decisions that might not represent various protected groups, resume screening and rating models will likely contain institutional and systemic biases.

Additionally, these systems, which are typically NLP-based, can produce harmful content, propagate stereotypes, or unbalanced portrayals of other populations. For example, since they were learned from Google News headlines, widely used word embedding architectures that represent text data as vectors to be taught by neural networks were discovered to have gendered stereotypes in 2016. Afterwards, it was discovered that GPT-3 produced extremely powerful, unfavourable prejudices about religious groups [1].

Additionally, the bias of other LLMs, such as GPT-4 and BERT, has been challenged. Both employers and job seekers may suffer as a result of these biases. If discrimination results in the placement of less qualified candidates in a position, more time and money may be spent on training and onboarding, ultimately resulting in decreased employee retention and satisfaction [95]. Most academics have concentrated on developing strategies for detecting and reducing bias to assess the significance of screening procedures. For instance, authors [84] introduce a test algorithm for resume screening that can detect bias in candidate scores under five distinct protected attribute scenarios. Similarly, authors [35] reduce prejudice by using resume-to-job-description matching to reweight tf-idf values on fairness criteria [22] introduces a mitigation process through candidate ranking.

2) Interviewing Prospects. The third phase in the hiring process is interviewing candidates to learn more about their KSAOs, work values, personalities, and other characteristics. Over the last ten years, AI has become increasingly used in the employment process to assess these qualities through interviews. Numerous AI modalities have been employed, such as web-based Q&A assessments, automated video and phone interviews, and chatbots for applicant interaction [85]. For example, businesses like HireVue. Additionally, Bright Hire uses artificial Intelligence (AI) to grade video interviews and assign hiring fit and personality scores to prospects. However, bias has been recognised as a problem in AI applications based on images and videos, as noted in multiple research [29, 69, 104]. This issue came into the limelight after HireVue stopped using its video-based candidate scoring practices in 2021, primarily due to a lack of transparency in AI decision-making [71]. In 2020, Illinois passed the Artificial Intelligence Video Interview Act, the initial law addressing AI applied in work interviews. According to the act, businesses must notify applicants that an AI system will review their interview, disclose the traits the system would use to score, and seek each applicant's consent before undertaking the interview.

3) Choosing and Assessing. The final step in the recruitment process is selecting one or more candidates for the job and negotiating the offer, which is used to quantify the overall recruitment process of the company. Artificial Intelligence (AI) has been used in various shapes and sizes to support selection and job offer negotiation. For instance, AI recommends salaries and training in negotiating job offers, speeding up the hiring process [18]. This is best illustrated through products like Oracle Recruiting Cloud; not only does it calculate the likelihood of a candidate accepting an offer, but it also enables firms to experiment with different ranges of compensation, benefits, and other forms of incentive to maximise the odds of acceptance. Automate numerous negotiation processes, e.g., contract and compensation, based on multiple factors, including labour market projections.

AI in Recruitment: Benefits and Drawbacks. Through machine learning technology-enabled screening of heavy application data, AI recruitment software revolutionised the recruitment process and allowed companies to match applicants by experience, capability, and prospective traits [85]. The application increases productivity by removing inefficient tasks, containing recruitment expenses, and improving fact-based decision-making [97]. AI hiring tools can accelerate hiring and increase scalability through resume screening, candidate fit assessment, and even first-round interviews. Yet, these breakthroughs come with some frightening challenges. Perhaps the biggest one is the lack of interpretability and transparency of AI-based hiring. Most machine learning models are "black boxes" because it may be hard to comprehend how precisely they make certain hiring decisions. This opacity is an ethical concern, especially when AI-driven results are based on biased historical data that privilege majority groups and discriminate against minority groups. AI programs can reinforce discriminatory hiring practices inadvertently if training data has social biases.

Furthermore, the application of AI in hiring is further complicated by ethics and regulatory challenges. The Equal Employment Opportunity Act and the GDPR (General Data Protection Regulation) are regulations that focus on accountability and fairness. Yet, firms cannot impose AI hiring practices that adhere to these regulations. Ensuring fairness involves ongoing vigilance against biases, transparency of algorithms in decision-making, and human oversight to correct AI-driven discrimination. While AI improves hiring effectiveness, its ethical dangers require careful application to ensure fairness, diversity, and legality.

The drawbacks of AI selection and hiring. More and more articles bemoan the use of AI software in the recruitment and selection process, even as these are touted as promises of technology. What is significant here is that hefty costs accompany the innovation and application of the technology, so big businesses have a competitive edge. Small and medium-sized businesses cannot afford to take advantage of their benefits. In addition, if AI use were to be functional, it would have to handle sensitive and personal data, invading applicants' privacy and data security and subjecting them to discrimination, marginalisation, and social stigmatisation [25, 67]. This is important because AI technologies can support actions that violate fundamental rights and will operate in a way that makes judgments too complicated for humans to understand fully [45, 52]. As a result, accountability and responsibility may be undermined by the technology's lack of transparency and explanation. Due to these problems, some HR professionals are also dubious about using AI-based technologies for hiring and job selection processes, believing that they will more likely endanger their career prospects than help them [28, 88]. The evidence focuses on the reaction of job applicants because it attempts to extensively study the application of AI tools in selection and recruitment. A part of this is studying the emotions, attitudes, and behaviours that result from their engagement with AI-based hiring and selection processes. Empirical studies in this area have shown contradictory results about how job seekers view diversity bias and fairness when interacting with AI systems. However, many academics are hopeful that job seekers will embrace AI applications. Candidates for jobs seem to link the employment of AI applications to innovation, which increases their appeal to employers [41]. Some academics say AI-based hiring and selection practices are unfair to job hopefuls [68]. For instance, the scholars in a current study that probed some candidates' knowledge about fairness and attitude towards AI reviews stressed that they would be more comfortable continuing to have the role of human beings in the evaluation process [77]. To this end, the interviewees were more likely to choose the 'devil they knew' over the 'unknown devil' in the guise of the algorithm, even though they acknowledged that human beings have inherent prejudices. Other research indicates that job seekers are dissatisfied with the impersonality of AI-based hiring and selection procedures, which tends to discourage people from applying to new positions. Lack of knowledge about the technology is another factor that makes job seekers believe negatively in the employment of AI applications in the recruitment and selection process. This mindset may be strongly related to the reluctance to provide details on the technology's internal workings, creation, and use. In the foregoing context, transparency refers to releasing information about the selection and recruitment process to enhance its predictability and ease of understanding for applicants [65]. Applicants are usually concerned about privacy and data protection issues and fear of discrimination [66]. Within a professional network society, frequently facilitated by AI, such as in LinkedIn, this technology, some researchers are pointing out, can be a two-edged sword: on the one hand, it can bring job seekers and opportunities into view, while on the other hand, it introduces new types of risks by keeping them from adjusting the scope and nature of the information they convey concerning the audience, context, or degree of the relationship created. Artificial Intelligence (AI) technology is being developed and implemented in increasing amounts to undertake various tasks in hiring and selecting. However, with such development and implementation, the needs and restrictions of the organisation, implementer, and astute first-time implementer practically violate core rights. The competitors also have the typical problems of possible rights violations and prejudice against diversity, as well as the demand for innovation and greater efficiency. In response, the next section explores what can be referred to as fairness in applying AI in the hiring process.

Fairness Metrics and Bias Mitigation Strategies. AI recruitment fairness is quantified based on several key measures, such as disparate impact, which tests for differences in selection rates between protected groups. Equalised odds, which attain balanced error rates between groups. Demographic parity, which attains balanced hiring rates between multiple applicants. Methods like reweighting training data, adversarial debiasing, and fairness-aware machine learning have been developed to offset bias [109]. These approaches help create more equitable hiring processes by reducing discriminatory patterns embedded in AI-based selection models.

1) Defining AI-powered equity in hiring and selection: The stakeholders' viewpoints. According to the discussion above, technology innovation has gradually affected the hiring and selection process to assist HR professionals and improve productivity. However, it also demonstrated how this endeavour is accompanied by several limitations that may significantly exacerbate the perception of AI technology's unfairness in hiring, particularly regarding privacy infringement and social prejudice against job searchers. However, these constraints vary in importance based on one's interest in the recruiting process, and fairness is a relative concept whose definition is shaped and constructed by one's experience and assumptions that varyingly apply to candidates and HR representatives. Based on one's observation, issues about transgression scenarios get more complex, and this section demonstrates that fairness is complex and relative based on one's position in the hiring and selection process. That is, perceptions from various stakeholders significantly influence the view of the fairness of the selection and hiring process. An increasing number of scholarly publications corroborate the dynamic state of fairness and support that fairness perceptions change throughout the hiring and selection process [23, 61, 62].

2) Fairness of AI-powered hiring practices: A legal viewpoint. Assuming that the purpose of the law is to coordinate human behaviour and inform human beliefs, it serves an expressive role [72, 80]. It is possible to say that the existing rules can be used as a template to lead us through the conflicting perceptions of fairness among the different stakeholders in the AI-powered recruitment and selection process. In the advanced context of AI-powered employment, they can be used as a normative foundation, influencing behaviour and fostering mutual respect for fairness.

Research Gap. Although much research has been done on the subject, there are still some open questions regarding the long-term impact of AI hiring on diversity and inclusion in the workplace. Current work focuses on detecting bias but lacks holistic frameworks to mitigate bias in real-time AI-driven decision-making. Moreover, most studies treat the fairness of AI from a Western perspective without considering variations within regions when AI is used for recruitment. Also, there is sparse concrete information regarding how job applicants perceive AI-driven hiring processes or how they impact the applicant journey. Future research must incorporate human-AI partnerships in hiring to harmonise automation and moral, just hiring processes.

Theoretical Framework. The Fair Machine Learning (FML) framework, as [13] theorises, is the optimal theoretical framework for creating AI-driven hiring tools that identify and counteract candidate choice biases. The FML approach incorporates fairness constraints into machine learning models to generate fair decision-making without sacrificing predictive power. It highlights three principal bias mitigation strategies: pre-processing, which transforms training data to remove historical biases; in-processing, which adjusts learning algorithms to incorporate fairness constraints; and post-processing, which corrects biased outcomes after predictions have already been generated. Applying this system to AI-powered recruitment ensures that recruitment models do not sustain historical discrimination. For instance, AI hiring software often relies on past employment data, which will contain inherent gender and racial biases. These biases will continue to be a disadvantage of protected groups. By including fairness-aware changes like equalised odds and demographic parity, the FML strategy avoids this and maintains equal selection rates for all groups. To ensure accountability in AI hiring, the approach also complies with ethical AI standards and legal guidelines like the Equal Employment Opportunity Act and the General Data Protection Regulation (GDPR) policy. Employers can use the Fair Machine Learning approach to develop AI hiring tools that optimise productivity and ensure equity and fairness in candidate selection.

METHODOLOGY

This chapter outlines the research methodology followed to investigate algorithmic fairness in hiring, focusing on designing AI-based recruitment software capable of identifying and mitigating candidate bias during recruitment. The study follows a purely secondary research method, devoid of primary data collection, based on available datasets and literature to investigate recruitment algorithm bias. Statistical analysis is performed in SPSS to interpret patterns, correlations, and hiring bias trends. The chapter covers ethical issues, research design, data collection and analysis procedures, and the rationale for methodological decisions.

Research Design. This study employs a quantitative research design because it objectively examines bias in AI recruitment tools using numerical data [31]. Thus, this study objectively assesses bias in AI hiring tools and the efficacy of fairness interventions. The impact of current AI recruitment methods on applicant decision fairness is investigated using a descriptive research design. The study analyses algorithmic bias and fairness metrics using statistical and computational methods. The research is purely secondary-based, and available datasets from valid sources like peer-reviewed journals, research gate complete materials, government reports, and industry studies on AI-based recruitment processes are used. Quantitative analysis allows statistical calculation of algorithmic fairness and effectiveness of measures against bias in employee recruitment. Quantitative analysis reiterates that various candidates equate what they understand with fairness and being treated fairly and equally, assuming that their credentials, knowledge, and work productivity should presumably satisfy the HR practitioner hiring choice [44, 92, 99, 110]. They believe the recruiting process is fair to their experiences of honesty, integrity, and respect, emphasising the importance of interpersonal empathy and communication in the workplace and going above and beyond the law to ensure ethics and equity in hiring [59, 98]. However, job hopefuls are more likely to sense procedural fairness due to information asymmetry in most selection and recruitment processes. This implies that they are inclined to believe that the recruiting procedure produces equitable hiring outcomes. This kind of justice has been dubbed "procedural fairness," and its main popular tenets are as follows:

- Job relatedness: The hiring manager should consider only the information required for the position to assess the applicant's aptitude and skill better.

- Consistency: Every applicant should go through the same hiring procedure.

- Performance opportunity: During the hiring process, candidates should be allowed to demonstrate their abilities and expertise.

- Objectivity: To avoid subjective judgments or the personal opinions of HR professionals, the candidate must be assessed using relevant and objective criteria.

Due to the procedural nature of fairness, candidates' perceptions of fairness may vary depending on their experiences and whether recruiting and selection processes are AI-based or analogue. In general, negative views are linked to AI-based procedures [48, 58, 105], because job candidates believe they have less control and influence over AI-based processes than traditional ones [48]. On the other hand, other research found that people who experience social discrimination at work often think AI technologies will improve equity and make companies more appealing [58]. In summary, applicants evaluate fairness based on their experiences and some procedural fairness guidelines. AI employment presents challenges because of differing opinions, some of which are negative due to less control and others positive, especially for those discriminated against. Perhaps the answer to guaranteeing equitable hiring and selection at the social level is to balance these conflicting viewpoints.

Data Collection Methods. Since this study uses secondary data, information was taken from academic databases such as Google Scholar, IEEE Xplore, Springer, Research Gate, complete PDF materials, Academic journals, and ScienceDirect. Research examines datasets containing AI-driven employment outcomes, investigating racial, gender, and socioeconomic biases in candidate selection [74]. Researchers employ meta-analyses and systematic reviews of AI recruitment tools to enhance study validity.

Data Analysis Techniques. Researchers employ SPSS to analyse collected data, a statistical tool recognised for applicability in quantitative research. Applying descriptive statistics alongside correlation analysis and regression modelling in SPSS enables researchers to detect biased patterns. The fundamental statistical methods consist of:

- Descriptive Statistics: Utilised to create visual representations and summaries of recruitment patterns.

- The application of Chi-Square Tests serves to ascertain the statistical significance of biases in candidate selection processes.

- Regression Analysis: Utilised to evaluate connections between algorithmic variables and hiring outcomes.

Using these methods, researchers may objectively evaluate the effect of AI-powered hiring tools on biases in the hiring process.

Ethical Considerations. The study's dependence on secondary data necessitates ethical compliance that ensures data credibility while maintaining proper citation practices and adherence to open-access policies. According to the British Psychological Society's ethical rules, the study procedures refrain from exploiting private or sensitive data [98]. An ethical analysis of AI recruiting tool bias examines how algorithmic decision-making impacts inclusion, equity, and diversity.

Rationale for Methodological Choices. The study aims to examine preexisting data and detect bias patterns through non-intrusive methods, which supports secondary quantitative research approaches [21]. SPSS utilisation strengthens statistical interpretation accuracy while offering a solid structure to assess recruitment algorithm fairness. This approach guarantees that results remain grounded in evidence while being reproducible and applicable to scholarly discourse and industry conversations about ethical AI hiring methods.

The research methodology used to examine bias in AI recruitment tools has been thoroughly detailed in this chapter. This study achieves objective data-driven insights into algorithmic fairness by implementing a secondary quantitative research method combined with SPSS statistical analysis. The subsequent section delivers the research outcomes and their corresponding interpretations derived from data analysis.

RESULTS AND DISCUSSION

This chapter will give comprehensive details on the conducted analysis and the conclusions drawn from the data analysis. For ease of identification, tables will be created with the main phrases used, their frequency of occurrence, the author, and the findings. To determine the relationship and the fairness of the algorithm used in hiring, this chapter will employ both linear regression analysis and Pearson correlation.

Table 1 – Displays the conceptual analysis of secondary source keywords (Sources - Google Scholar)

Keywords	Search Found	Search Screened	Search Utilised	Author	Findings
Bias	60	10	2	[85]	AI-powered resume screening systems can potentially reinforce workplace inequities by displaying notable bias against candidates from underrepresented groups.
Recruitment	38	8	3	[89] [3]	Integrating explainable XAI in recruitment is a technical challenge and an ethical imperative. Building trust, guaranteeing justice, and adhering to legal and ethical requirements all depend on the ability to explain AI choices.
Hiring	206	30	4	[63]	Hiring methods that neglect individual differences due to aggregation bias are inappropriate in diverse situations.
Candidate	76	10	2	[12]	A candidate's fit with the company and expected performance level after hiring is usually determined by factors like employee motivation, person-job fit, and anticipated duration.
Artificial Intelligence	30	9	1	[108] [85]	The artificial intelligence recruiting process relies on date-based selections, which inherently have fewer biases than human-based selections. Human recruiters could miss patterns and trends that artificial Intelligence can identify.
Fairness	54	20	2	[23]	An increasing corpus of academic research emphasises how fairness is dynamic and suggests that how fairness is seen changes throughout the many stages of recruitment and selection.

The data collection procedure is detailed in the above table. Peer-reviewed articles from Google Scholar and corporate reports are among the secondary data sources used in this study. The keywords listed in the above table served as the inclusive criterion for classifying and screening the journals that were the subject of the investigation.

Table 2 displays the descriptive statistics for word frequency and interpretation variables.

Table 2 – Descriptive statistics

Variable	Mean	Std. Deviation
Word interpretation	18.33	11.325
Word frequency	77.33	65.099

Using the word interpretation, the mean was 18.33, and the standard deviation. A deviation of 11.325 was obtained. The standard deviation of the word frequency was 65.099, whereas the mean was 77.33. This indicates that the average frequency of words was higher than the average interpretation of words.

Table 3 shows the Pearson correlation (r) between the word frequency and the word interpretation. The table indicates a moderate effect of hiring algorithm fairness, a word frequency and word meaning correlation of 0.058, and a p-value of 0.456 between the variables that are not statistically significant according to the table.

Table 3 – Correlation

		Word interpretation	Word frequency
Pearson correlation (r)	Word interpretation	1.00	0.058
	Word frequency	0.058	1
Sig.	Word interpretation		0.456
	Word frequency	0.456	
N	Word interpretation	6	6
	Word frequency	6	6

Table 4 – Model summary

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
1	0.058a	0.33	0.246	72.659

Notes: Predicators (constant) – word frequency

Although the R2, also known as the coefficient of determination, reveals how much variance is explained by the variable used, the model table shows that the R-value, corresponding to the Pearson correlation, is 0.058.

The fact that 0.33 equals 33% suggests that word frequency is a reasonable indicator of the algorithm's level of fairness in hiring.

Table 5 – ANOVA

Model	Sum of squares	DF	Mean square	F	Sig
Regression	72.300	1	72.300	0.014	0.912b
Residual	21117.033	4	5279.258		
Total	21189.33	5			

Notes: Dependent variable: word interpretation; Predictors (constant) – word frequency.

Table 5 demonstrates the ANOVA between the regression on algorithm fairness in hiring and the creation of AI-powered recruiting tools to detect and lessen biases in selecting candidates.

The ANOVA table provides more information than the descriptive analysis mean and standard deviation. According to the F value of 0.014 in the bale, there may be a relationship between the chosen terms. It also implies that there may be a significant association between the frequencies of terms, but the significant level of 0.912 indicates that this relationship is not statistically significant.

This study used content analysis as its methodology. Nonetheless, qualitative and quantitative research can use this approach [38]. Additionally, it acknowledges the importance of the information in texts, words, phrases, and language used in speeches. Content analysis can be used for significant but challenging research topics in which management and technology academics are interested. Content analysis (computer-aided text analysis) is structured to support and enhance the work with tested material by categorising, organising, and providing search capabilities. Additionally, content analysis enhances synthesised data discovery, analysis, and display.

Findings from each research question are described in light of the literature. According to this study's findings, artificial Intelligence can detect minor patterns humans cannot detect throughout the screening procedure. This agrees with the report by [85] that artificial Intelligence can spot patterns and trends that might not be noticeable to human recruiters. The bias problem in this study can be resolved by the hiring procedure that employs the artificial intelligence method described in this study. This agrees with the report by [108] that hiring through artificial Intelligence depends on making choices based on data, which naturally have fewer prejudices than decisions made by people. The findings agreed with what [15] reported: web-based jobs utilised collecting a list of job vacancies with dates, reaching a handful of prospective candidates.

The Pearson correlation (r) of 0.058 suggests the existence of a positive correlation between keyword frequency and its interpretation. However, such a correlation can be deduced to suggest that artificial Intelligence can reduce bias in recruiting new job candidates. The R^2 value of 33% suggests that the keyword utilised in this study served as a fair predictor in assessing the fairness of algorithms in the recruitment process. This agrees with the findings by [51] that Artificial Intelligence performs better than human counterparts in screening job applications due to its capacity to hasten the process and pull out specific skills and personality traits from a candidate's digital footprint, including their online presence on social media platforms.

Additionally, the results of this study imply that AI-powered resume screening systems may be highly biased against applicants from underrepresented groups, which could exacerbate inequalities in the workplace [85]. This agrees with the findings by [18] that institutional and systemic biases will most likely appear in resume screening and rating models because the training set relies on historical hiring decisions. This also agrees with the findings by [63] that aggregation bias is because hiring models ignore individual differences, making them unsuitable where diversity is involved.

CONCLUSIONS

Modern organisations have experienced major recruitment system developments because Artificial Intelligence (AI) has become integrated into their processes. AI technologies have boosted recruiting processes through automation, yet they have brought about substantial obstacles in improving efficiency. The main challenge with AI recruitment systems originates from their tendency to perpetuate biases from historical data when making selection decisions. The use of biased input data creates serious problems because it perpetuates discrimination against minority groups in employment selection. Although they present barriers, AI recruitment systems can improve fairness and efficiency in hiring without bias due to historical data. The research findings merge previous chapters to show an overview of the study work, which delivers useful approaches that enhance impartiality within AI-powered recruitment tools.

The study's findings suggest several ideas for improving the fairness and transparency of the AI recruitment process. The research mainly examined the issues of fairness and bias that arise from AI-based recruitment systems. The research bases its findings on statistical evaluation of secondary data to determine how well AI systems achieve fairness in hiring and minimise discriminatory behaviour. The research analysed how recruitment algorithms occasionally maintain societal biases, causing discrimination against minority groups throughout its analysis. The analysis demonstrated that AI recruitment platforms present opportunities for efficient operations but need proper supervision to stop discriminatory results. This careful evaluation of secondary materials disclosed AI's double nature for enhancing diversity in recruitment because studies demonstrated its ability to make fair hiring decisions. Other studies also exposed its potential to maintain biases and discriminatory practices. The analysis used SPSS for regression and correlation analysis to evaluate methodological aspects of algorithmic recruitment processes. A thorough investigation took place to address ethical matters regarding AI's system transparency and responsibility in employment selection. The complete study shows that AI could enhance recruitment but demands thorough supervision and continuous development to achieve fairness.

Because XAI technology allows for complete process transparency for AI system decision-making, organisations must implement it. The realisation of XAI systems supports candidate trust development because it reveals the processing mechanics behind application evaluations. The assessment of AI tools needs to be conducted through continual monitoring and auditing practices. A process of persistent algorithm inspection and needed corrections to avoid bias will help maintain the fair development of these systems. Organisations must focus on creating training data that presents diverse representations because this practice will help prevent AI models from developing biased outputs. Human evaluators should monitor AI recruitment processes as a recommended solution. The decision-making authority for final hiring selections should belong to humans because they need to assess the unique characteristics of candidate profiles whose evaluation AI systems alone may fail to capture completely. To protect fairness standards, developing legal structures that monitor the compliance of AI recruitment tools with established criteria is mandatory. The creation of employee training programs for ethical AI practice should be a company priority because AI recruitment systems need continuous improvement.

Multiple constraints exist regarding the findings, which provide essential knowledge about AI recruitment methods and potential bias reduction capabilities. The research depends mostly on secondhand data collection sources, including literature review results, although this extensive approach fails to reflect the detailed aspects of practical AI recruitment implementation. Because the data is secondary, researchers cannot directly observe how organisational personnel implement or experience these recruitment tools. When researchers utilise SPSS to run statistical tests, they successfully identify important relationships. Still, the tool does not replicate the complete human decision-making approach and subtle decision-making biases in artificial intelligence models. The study suffers from its concentration on particular AI recruitment tools since it fails to evaluate other upcoming technologies and alternative approaches to recruitment management. Most of the data comes from perspectives obtained in developed countries, particularly the US and the UK, as these countries are at the forefront of deploying AI recruitment systems today. The study might not provide enough insight into the unique regulatory, cultural and social environments in regions that recently adopted AI in recruitment procedures. The legal complexities that arise from AI adoption worldwide need extra attention to maintain fairness in international recruitment environments. Research into AI recruitment systems requires additional work because of several critical restrictions, especially concerning practical implementation, multi-national studies, and robust ethical and legal framework analysis.

Several benefits and challenges associated with using AI systems for hiring must be addressed. AI adoption gives businesses additional resources to advance hiring procedures toward more rapid, scalable, data-driven decision-making. AI systems run the risk of reproducing existing social biases during operations, which results in biased hiring decisions for particular demographic groups. Research evidence shows that AI recruitment tools support organisations in making unbiased selection choices, yet these systems operate under the same influences of human bias. AI-based recruitment tools need proper design and testing conditions, as well as transparency features for organisations to establish fair hiring systems. Detection measures alongside diverse training material and human supervision are crucial to reducing unfair discrimination from emerging as a results-based issue. These issues must be resolved if organisations are to reap the full benefits of AI in developing hiring systems that support equality and fairness throughout the hiring process. The successful implementation of AI in recruitment activities is essential to the future of impartial hiring practices.

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