

DEHUMANIZATION AND LIMITS OF ARTIFICIAL INTELLIGENCE WITHIN
RECRUITING: THE OPTIMAL INTERACTION BETWEEN HUMANS AND
ARTIFICIAL INTELLIGENCE

by

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DISSERTATION

Presented to the Swiss School of Business and Management Geneva

In Partial Fulfillment

Of the Requirements

For the Degree

DOCTOR OF BUSINESS ADMINISTRATION

SWISS SCHOOL OF BUSINESS AND MANAGEMENT GENEVA

November, 2024

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Dedication

This dissertation is lovingly dedicated to my children, whose joy, curiosity, and unconditional love inspire me every day. You are the reason I strive to grow and achieve.

To the memory of my father, whose guidance, strength, and values continue to shape who I am. Though you are no longer with us, your influence and love remain deeply present in my life and work.

To my mother, for her unwavering support and wisdom, and to my mentors and colleagues, for their encouragement and insights that have enriched this journey.

Finally, to the world of recruitment and all those striving to find the balance between humanity and innovation, may this work contribute to creating a future where artificial intelligence enhances, rather than diminishes, the human connection.

Acknowledgements

First and foremost, I would like to express my heartfelt gratitude to my family. To my children, whose love and laughter have been a constant source of motivation, and to my mother, whose unwavering support and encouragement have been a pillar of strength throughout this journey. To the memory of my late father, whose wisdom and values have guided me even in his absence—I dedicate this accomplishment to your enduring influence.

I am deeply thankful to my academic advisors and mentors, whose guidance, patience, and insights have been invaluable. Your belief in my work and constructive feedback have helped shape this dissertation into what it is today.

I also extend my sincere appreciation to my colleagues, peers, and the participants in my research, whose contributions and engagement brought depth and richness to my study.

Finally, I am grateful to my friends and everyone who supported me, directly or indirectly, along this path. This work would not have been possible without your encouragement, kindness, and understanding.

Thank you all for being part of this journey with me.

ABSTRACT

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2024

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Artificial intelligence (AI) is reshaping the recruitment landscape by enhancing efficiency, scalability, and accuracy. However, its adoption brings forth significant ethical dilemmas, such as dehumanization, bias, and transparency challenges. This dissertation delves into these issues within recruitment processes, aiming to find a harmonious interaction between AI and human recruiters.

The study emphasizes the advantages of AI, including the automation of repetitive tasks, improved candidate matching through predictive analytics, and cost savings. Simultaneously, it points out critical drawbacks, such as the reinforcement of biases from historical data, a lack of personalization, and concerns regarding candidate data privacy. Dehumanization—the decline of empathy and personal connection in hiring emerges as a

significant concern, potentially harming employer-employee relationships and negatively impacting the candidate experience.

Employing a mixed-methods approach, the research combines qualitative and quantitative data to explore these issues. Interviews with HR professionals and AI specialists reveal a shared understanding of the necessity for a balanced strategy in AI integration. Statistical analyses further highlight the importance of transparency and fairness in reducing bias and building trust.

The dissertation suggests a hybrid recruitment model that merges AI's efficiency with human insight. This model prioritizes fairness audits, explainable AI systems, and ethical oversight to strike a balance between automation and empathy. Practical recommendations include training AI systems on diverse datasets, utilizing fairness-aware algorithms, and encouraging collaboration between human recruiters and AI technologies.

This research adds to the academic and professional conversation by tackling the ethical and operational challenges that AI presents in recruitment. It provides actionable insights for HR professionals, AI developers, and policymakers to enhance recruitment processes while maintaining humanity and fairness.

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CHAPTER I: INTRODUCTION

1.1 Background and Importance

In the past decade, the entire recruitment scenario has undergone a drastic change due to the implementation of artificial intelligence (AI) (Iqbal, 2018). Recruitment has been a labour- intensive and human judgment-dominated process historically. The traditional approach to these procedures is very personal; however, it is inefficient, time-consuming, and prone to biases. This has been revolutionized with the coming of AI, which is an entirely data-driven way that increases efficiency and precision in selecting candidates. AI technologies, from machine-learning algorithms and natural language processing to predictive analytics, have optimized various recruitment processes: resume screening, candidate matching, interview scheduling, and assessment of candidates.

However, the inclusion of AI in recruitment is not without its challenges. Dehumanization is the biggest problem because of the critical masses of candidates (Fritts, 2021). Dehumanization involves reducing a person to nothing more than data and removing the human touch from individualized interactions. The phenomenon leads to alienation in candidates, undermining the experience and potentially turning top talent away from participating in the recruitment process. This, therefore, represents the delicate balance that contemporary organizations need to strike in harnessing AI for its strengths and in a manner that still maintains a human touch.

Innovation, creation and expansion of markets, currently, is highly dependent on digital transformations. digital transformations are predominantly focused on making the competitive standing of a company more prominent and enhanced while also guiding the market evolution trajectory. Hence the application of Information Technology (IT) makes a vital contribution to digital transformation. Within the recruitment industry, IT plays a

key role in rationalizing and accelerating the hiring process while also broadening company reach to a wider pool of potential candidates (Wilfred, 2018; Al Bassam, 2023). Hence, IT has eventually become an indispensable part of the recruitment field.

Artificial Intelligence, most referred to as AI, is one of the most significant technological advancements in the last decade. AI is any machine or software that reads its environment, perceives it based on data available to it and produces outputs that maximizes the chances of positive outcomes to meet a set goal. IBM defines artificial intelligence as “Artificial intelligence, or AI, is technology that enables computers and machines to simulate human intelligence and problem-solving capabilities”. AI is highly advanced in nature, therefore, uses cognitive abilities such as problem-solving, calculations, and learning. AI takes on a multi-disciplinary approach and utilizes the fields of mathematics, computer, psychology, neuroscience, linguistics, philosophy to name a few. Tasks that were previously associated to humans such as the abilities to think and learn are now replicated using AI. Therefore, tasks that require intellect can now be solved with ease using AI machines or software. One popular example is ChatGPT- an AI based website that allows everyone to access data on the internet within seconds by just asking questions. ChatGPT has the ability to produce coherent and comprehensive answers in less than five seconds. As much as it may seem to have eased human lives, it has also led to people losing their jobs such as content writers, designers, data analysis related jobs etc. Companies have bought AI software to replace employees because it is cost-effective and efficient and does the job quicker. Every sector and industry highly seek the integration of AI into their processes, whether it be manufacturing, design, supply chain management, or just digitizing their business, AI is crucial and central to the advancement of an industry- or so it appears. By integrating AI, industries have decreased the time of production, increased manufacturing capabilities, however, cut down significantly on manpower as the roles have

been automated. This integration has now extended to talent acquisition using various AI-based talent management software such as ATS. Although there are conflicting opinions on AI in general, there is still a wide gap between understanding whether AI is making our lives easier or taking over human aspects of work. In recruitment processes, AI is being considered a key component. The aim of this study is to look at how Artificial Intelligence is impacting both the employers and the employees, the application and selection processes especially in the initial phases of hiring. The study will also look at dehumanizing factors, ethical considerations, and wider implications in the Human Resources industry.

1.2 Historical context of Human Resource and Recruitment

Human resources are “the set of people who make up the workforce of an organization, business sector, industry, or economy. A narrower concept is human capital, the knowledge and skills which the individuals’ command. Similar terms include manpower, labor, personnel, associates or simply: people” (Talwar & Agarwal, 2022). Together, all these factors make up the Human Resources Department (HR Department) in companies and their responsibilities include overlooking compliance to economic regulations, employee satisfaction, hiring and selection of new candidates, administrating employee benefits, and offboarding employees. Briefly, they act as the bridge between managerial aspect of companies with the people.

Recruitment is considered a product of World War II as a result of men drafted for war and a shortage of working force in various industries. Thus, companies introduced calls for employment for both men and women through “staffing agencies” (Prince Perelson, 2024). However, Human Resources Management, which is associated with talent acquisition and staff management dates back to the 18th century. In the Guild system of England in the 18th century, new roles were given to “Family Officers” such as bookkeeping, keeping account records, management of the staff, and delegating tasks

belonged to these Family Officers. Payne (2023) suggests that this was the official beginning of the “personnel” approach to regulating work in companies. But the most significant human resources advancement happened in the Industrial Age because of the rapid growth of industries such as railways, mass hiring began with the increasing need for new mid to low tier companies to manage these big and emerging industries. This revolution also led to “Scientific Management” which meant that departments were established within organizations to manage large numbers of staff doing varying tasks. In the long run, this meant producing maximum output and minimizing costs associated with the processes, but little to no attention was paid to employee needs. In the post-industrial era, modern Human Resource practices were introduced where employee needs were also met which led to the industrial psychology movement and the concept of human relations. This also led to “organizational development” which focused on comprehending business goals through empirical research and data. This advancement paired with emergence of computers and technology revolutionized administrative tasks within organizations. Increased automation of complex processes instead of manual data entry or the use of paper and pen streamlined administration and communication between departments. Because processes were automated, success also became measurable (Payne, 2023).

Table 1 Development of Human Resource Management between 18th Century and 21st Century.

Time Period	Developments in HR	Impact on Organizations
18th Century	Introduction of “Family Officers” for delegation of tasks. Delegation of new roles in the British Guild Systems.	Introduced accountability and structure to organizations And promoted “specialization”.

19th Century- Industrial Revolution	Scientific management New departments developed for rapid growth of companies Adoption of regulations and policies to manage mass hiring processes.	Promoted efficiency but worker needs were not being met. Increased development and expansion of businesses.
Post-Industrial Revolution	Introduction of Industrial Psychology HR established Worker needs prioritized	Contributed to looking after employee needs, to boost morale, and increased employee engagement
Organizational Development Era	Introduction to business research Integrating HR with business research and objectives Evidence-based growth techniques utilized	Improved job satisfaction Sustainable business practices
Digital Age	Introduction to automation of industry processes Increased use of analytical data Digitalization of HR processes Advent of HR analytics	Increase in efficiency Enhanced communication Measurable success

Source (Payne, 2023)

1.3 AI's role in revolutionizing recruitment

Artificial Intelligence has countless benefits, but the most important benefit is AI's ability to replicate decision-making without having human shortcomings such as emotions, fatigue, brain fog, bias, and temporal and spatial limitations. AI also generates consistent results each time which means it can take over the job of multiple human workers without producing biased results each time. Similarly, machines also can manage and organize data better than humans, without error. Because such machines are better equipped at detecting anomalies or errors, they can also manage very large amounts of data which may cost companies a lot in terms of resources, time and energy if it were to be done by humans.

Hence, briefly, it is evident that AI has the ability to contribute greatly to the field of recruitment.

In the field of recruiting, AI mainly plays a greater role in repetitive tasks such as screening, assessing resumes, sourcing of resumes, and scheduling interviews with candidates. Within the sourcing phase, because it is a time-consuming process to screen thousands of resumes, AI makes the job easier. According to Wilfred (2018), sourcing is the most time-consuming part where 75% to 80% resumes get rejected in various stages of the hiring process so ultimately, implementing AI helps “standardizing the process so as to be able to assess a candidate’s skills and abilities more objectively without letting the inherent human biases interfere”. In the screening phase it is challenging to pick the right candidates from a large pool of applications. Wilfred (2018) states from his research that 50% of the recruiters believe that screening is the hardest phase of the recruitment process. Ibrahim and Hassan (2019) explore the Malaysian government’s talent acquisition phase for civil engineers and conclude that for 74 vacancies, 17000 people applied and only 2575 candidates were shortlisted with the help of AI. Had this job been given to an employee to do, it would have easily taken weeks to skim through thousands of applications. A similar model can be seen on LinkedIn, a famous web and mobile application that allows professionals from all over the world to connect. Because LinkedIn is AI-powered job search engine, It has made It easier for recruiters to collect applications in the shape of candidate profiles, and only choose the ones that match their keyword search. For small and medium-sized companies that may not have the funds to hire a third-party investor, platforms like LinkedIn have made the talent acquisition

process easier. Additionally, this has allowed employers to seek applications from both local and international markets, overcoming the barrier of communication. Additionally, AI-powered chatbots have proven to be a great tool for conversations with

applicants who want more information on their desired role, reply to inquiries, and to engage applicants in the hiring process (Wilfred, 2018; Talwar & Agarwal, 2023). This immediate feedback eliminates the need to wait long times on call or for email replies from the HR. Chatbots enable real time engagement with candidates, like Siri or Alexa, these chatbots understand and respond to messages by utilizing natural language processing (Ibrahim & Hassan, 2019).

However, with countless pros being studied about the use of AI in recruitment, the current debate surrounds the dehumanization aspect of the AI when it comes to talent acquisition. The increasing use of AI recruiting tools to expand efficiency is also being adopted by big companies like Microsoft, Unilever, KPMG etc. because of the large number of incoming applications due to the popularity of the companies.

1.4 Motivation for the Research

The dual needs drive the study; on one side, there is the need to harness AI benefits within the recruitment domain; then, there is the second need to mitigate the risks associated with human candidate dehumanization. As organizations have to keep up with the pace of this quickly changing job market, AI efficiency and accuracy become indispensable. Nevertheless, reliance on AI can be too much to the extent that the recruitment process may lose such human elements as empathy, intuition, or personal touch. Therefore, this research will try to investigate how AI can be made complementary to the human recruiter without replacing them entirely by making sure that the integration brings enhancement to the whole recruitment experience.

The implication of the findings in the study is therefore relevant in two areas, namely, industrial application and the establishment of knowledge in the area. Organizations have an increased interest in understanding how to work out their

recruitment process to get the best talent and retain it. Understanding how to balance AI and human interaction could lead to more effective and humane recruitment strategies, improving candidate satisfaction and organizational outcomes. From the standpoint of increasing knowledge, this study will add to the thriving body of knowledge regarding AI in hiring by providing insights into the ethical and practical considerations applicable to its implementation.

The integration of AI in recruitment offers numerous advantages, including increased efficiency, reduced bias, and improved candidate matching (Ore, 2022). AI-driven tools can process vast volumes of applications instantly, zeroing in on the best candidates according to predefined criteria (Bhalgat, 2019). They can even predict candidate success in comparison with historical data. This will slash much of the time and resources used for recruitment and be left to deal with strategic issues. The advantages of AI must be considered against potential adverse effects, however. A significant concern is that of dehumanization. Automated systems can achieve the best results, but they lack the power of personalized feedback and the ability to engage the candidate in an undoubtedly human manner. This can introduce the aspect of a poor candidate experience, whereby the people feel like they are talking to a machine and not a person. AI systems are also imperfect and, with unchecked supervision, could facilitate the continuation of biases.

To respond to these concerns, it is essential to develop a balanced recruiting strategy, leveraging AI's strengths while preserving its human elements. This study, therefore, seeks to outline best practices that will help in the integration of AI in recruitment so that both efficiency and a good candidate experience are upheld. This is set to provide meaningful guidance to organizations that will be considering the implementation of AI in the recruitment process.

1.5 Benefits of AI

The significant advantage of AI for recruitment is the considerable improvement of efficiency as well as speed in the hiring process. The traditional technique used to recruit people often involves activities such as going through resumes manually, having initial interviews with them or working alongside different stakeholders. As important but, they can make the recruitment cycle longer resulting in delays to critical positions.

AI on the other hand has potential to take over and accelerate many of these processes, thereby speeding up the entire recruitment. For example, AI-based programs can quickly analyse thousands of resumes within a fraction of time it would have taken a human recruiter thus identifying relevant candidates based on pre-set criteria (Prabhakar, 2023). Moreover, this mechanisation helps relieve HR professionals' burden while also reducing hiring lead time significantly –thus permitting organisations to fill their vacancies faster and more effectively than before.

Furthermore, AI may streamline candidate communication through automated responses and updates, which ensure that candidates are informed during recruitment. This helps to enhance the candidate experience as well as maintain a positive employer brand since job seekers would consider favorably companies that keep them engaged and informed (Allal-Chérif et al., 2021).

1.5.1. Superior Candidate Selection and Accuracy

AI also boosts the accuracy and efficacy of the candidate selection process besides simply enhancing efficiency. Keyword searches or subjective judgments by recruiters are often used in normal recruitment methods, leading to inconsistencies and biases. In contrast, AI employs complex algorithms that analyse diverse data points concerning a candidate's employment history, education background and even online activities in order

to determine how suitable they are for certain positions (Köchling and Wehner 2020). This data-driven approach helps achieve more objective and holistic evaluation of candidates. For example, artificial intelligence (AI) can observe things that human recruiters may not notice in the first place such as the correlation between specific skills and job performance. This leads to proper matching of candidates with job requirements which eventually enhances the quality of recruits and reduces staff turnover.

Moreover, AI systems are continually learning and improving themselves. By examining past hiring decisions, AI can adjust its algorithms to predict even more accurately whether or not a candidate is suitable for a job. Consequently, AI is an indispensable tool for organisations that want to fine-tune their recruitment strategies (Prabhakar, 2023).

1.5.2. The Cost Effectiveness

Another major advantage of AI in recruitment is cost saving potentialities. Traditional ways of recruiting are expensive as they comprise costs of advertising, recruiter's salaries, time spent on manual screening and interview among others. These expenses can accumulate fast, in particular for big firms with high staff turnover or those in competitive employment sectors.

AI systems are capable of reducing these expenses through automating most labor intensive parts of the recruitment process. For example, AI-powered chatbots can be used to deal with initial candidate interactions by answering questions, conducting primary interviews and even scheduling more interviews with human recruiters (Allal-Chérif et al., 2021). This mechanisation reduces the need for much human involvement at the beginning stages of recruitment thus allowing organisations to use their resources more efficiently.

Moreover, AI operates throughout unlike human recruiters whose time is limited by working hours. As such, candidate screening and initial assessments can go on even

after regular business hours thereby boosting efficiency while minimising time-related costs

Another thing is that this way saves money from manual labour resulting in bad hires. By improving the precision of choosing candidates AI decreases chances of wrong fit recruits. That makes the turnover rates decline together with rehiring and new employee training expenses (Brown et al., 2024)

1.5.3. Enhancing the Candidate Experience

AI is responsible for enhancing the experience of candidates as well as organisations. Traditionally, applicants wait for long periods without communication from the companies they have applied to. Lack of engagement like this one can breed frustration and negativity which could deter top talents from seeking opportunities there. During recruitment, these problems can be addressed by using AI to provide updates instantly and offer personalised services. For instance, an automated system driven by AI may send candidates' applications updates with their application status thereby reducing anxiety and uncertainty that come along with the job hunting process (Prabhakar, 2023). Additionally, feedback on assessments or interviews that indicate how a candidate has done can be given in real-time through artificial intelligence systems. By doing so the company will be able to communicate with its potential employees in different interactive aspects such including gamifying them and virtually assessing their abilities. To illustrate, businesses may use play-to-win games powered by Artificial Intelligence to measure fast thinking or innovative skills of a candidate in ways that are more dynamic and fun. Not only does it make the recruitment process more attractive to candidates, it also enables employers to evaluate abilities that would not be visible by traditional methods (Allal- Chérif et al., 2021). For instance, L'Oréal has utilized a serious game called Reveal. Through the use of

artificial intelligence, the game is designed to evaluate the abilities and suitability of candidates for the company. The corporate does not only lure superior people by gamifying the full employment process but also guarantees that chosen individuals coincide with its principles and cultural environment. Hiring activities could therefore be improved with respect to both effectiveness and efficiency (Allal-Chérif et al, 2021).

In addition, through AI, the recruitment process can be modified for every candidate so that they receive personalised job recommendations based on their skills, experience and ambitions. This approach will not only increase chances of finding a suitable match but will also influence the perception of a candidate about an employer as an organisation that cherishes its employees' needs and understands them.

1.6 Research Questions

Taking the aforementioned into consideration, the research questions that need to be addressed are as follows:

- How does AI improve the efficiency of recruitment processes?
- What are the ethical and transparency issues associated with AI in recruitment?
- How can organizations balance the use of AI with human interaction to maintain a fair and humane recruitment process?

1.7 Research Hypotheses

Following table includes the hypotheses that are based on the different research question which will be answered by the taken study in this dissertation.

Table 2 Hypotheses Considered for achieving

Research Question	Hypothesis
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How does AI improve the efficiency of recruitment processes?	H1: AI improves the efficiency of recruitment processes compared to traditional methods.
What are the ethical and transparency issues associated with AI in recruitment?	H2: Ethical concerns, such as lack of transparency and accountability, negatively affect trust in AI-based recruitment systems.
How can organizations balance the use of AI with human interaction to maintain a fair and humane recruitment process?	H3: A hybrid recruitment model (AI + human) provides better recruitment outcomes than AI-only or human-only methods.

1.8 Potential and Limitations of AI in Recruitment

The potential of AI in recruitment is vast. AI can streamline repetitive tasks, like resume screening, leaving recruiters more time for activities that positively influence their bottom lines (Chowdhury, 2023). Also, it can offer data-driven insights for organizations to make better hiring decisions (Stankevičiūtė, 2024). For instance, predictive analytics will be able to determine the candidates most likely to succeed in a given role based on historical data, and natural language processing could analyse the responses of the candidates to know which best suits the organization's culture. However, there are limitations to AI. After all, it depends on the quality of the data it is trained on; hence, biased data can contribute to biased decisions. In addition, AI cannot understand or get a nuance similarly to humans. This will lead to technically correct decisions but not in line with the values and culture within organizations. Moreover, the absence of human

interaction in the AI process might bring about a sense of dehumanization among the candidates, belittling their experience and harming the organization's reputation.

1.8.1 Reducing Recruitment Bias

Bias in recruitment has been a long-standing problem affecting hiring processes. Traditional methods of recruiting are largely dependent on human judgments thereby prone to unconscious bias arising from gender, age, ethnicity and educational backgrounds. These prejudices can result in discriminatory practices in hiring leading to lack of diversity in organisations and loss of the best talents. On this note, AI is capable of mitigating these biases since it focuses purely on relevant qualifications and experiences of potential candidates. Through analysis of objective data points, AI helps ensure that decisions made during hiring are driven by merit rather than subjective factors (Köchling & Wehner, 2020).

It is possible to have more varied and inclusive workforces because AI systems are not as likely to be influenced by stereotypes or personal preferences. Nevertheless, it should be noted that AI is not totally without prejudice. The problem of whether AI reduces bias will depend on the quality of data used in teaching its algorithms. If training data is biased, like say if it reflects a historical preference for candidates from certain backgrounds, then the AI system might unknowingly reinforce this bias through its recommendations. For this reason, organisations need to ensure that their AI systems are trained on diverse and representative datasets so as not to reinforce present inequalities (Brown et al., 2024).

An additional advantage of an AI system can be seen in potential biases within recruitment processes which need monitoring and addressing. By going through recruitment records, artificial intelligence can identify trends that may indicate discriminatory practices such as too many rejections among certain demographics individuals seeking employment. This permits firms to take corrective actions and make sure their hiring activities are conducted fairly.

AI is full of promises about enhanced efficiency, reduced bias as well as improved overall quality of hires. However, AI deployment in recruitment comes with a lot of challenges, risks and cons that must be addressed carefully so as to avoid unintended consequences. This detailed discussion comprehensively addresses these aspects.

1.8.2 Bias and Discrimination in AI-Driven Recruitment

The first most important danger of AI in hiring is perpetuating bias and discrimination. AI systems are created to learn from the past information, hence if the training data contains biases— whether related to gender, race, age or any other demographic characteristic—the AI system will likely reflect these biases in its decision-making process. In this regard, recruitment takes the centre stage given its emphasis on fairness and justice. For instance, if an AI system is trained on data where a particular demographic group has historically been underrepresented in certain roles, the AI may continue to favour candidates who fit the biased profile thereby perpetrating discriminatory hiring practices. This can present serious ethical and legal implications for organisations (Ore & Sposato, 2022). Amazon implemented an AI in their recruitment process. The company developed an AI- enabled hiring tool aimed at automating the screening of CVs. Nevertheless, this artificial intelligence tool was found to be deeply biased against women candidates in due course. For example, An AI system was taught on Amazon resumes for a decade primarily from male applicants. Therefore, the AI began to rate down CVs containing phrases like “women’s” as in “women’s chess club captain” and punished applicants who had attended female-only colleges. This example shows how bias in training data could lead to bigger and never-ending biases by AI tools. This case reveals that despite claims that AI will make the recruitment process more unbiased, it sometimes renews gender biases leading to unfair hiring decisions. In light of this serious problem, Amazon finally abandoned the AI tool showing how important ongoing supervision and

critical deliberation of limitations of AI technology is essential for recruitment (Ore & Sposato, 2022). Additionally, black box usually characterise many AI systems, meaning their decision- making practices are opaque. Therefore, it is difficult to find and correct prejudices, which may lead to a situation of unidentified systemic discrimination that results in damage (Brishti & Javed, 2020).

1.8.3 Loss of Human Touch and Personalization

For instance, AI systems can be very useful in processing numerous applications quickly for firms that usually receive thousands of job applications. However, personalization is lost as a result. Recruitment involves more than just matching qualifications with the needs of a job; it also requires understanding specific aspects of an applicant's personality, cultural compatibility and potential growth within the firm. AI-based platforms have the capability to filter resumes by finding candidates whose credentials match specific criteria but they could overlook such subjective elements. On the contrary human recruiters possess the ability to identify things that are not visible to machines like eagerness for certain roles or probable success in a high change environment (Dijkkamp, 2019). Therefore, there is reduced personalization hence less attractive candidate experience where individuals feel as though they are becoming a collection of data points rather than being evaluated on their own merits. This can lead to less satisfaction with the recruitment process and may discourage top talent from seeking jobs in organizations that heavily rely on AI for recruitment.

1.8.4 Data Privacy and Security Concerns

Recruitment involving AI often involves large-scale personal data collection, storage, and processing through resumes, cover letters, social media profiles, even psychometric test results. This has raised serious questions about data privacy and security. Companies must ensure that their AI system is compliant with data protection rules like

General Data Protection Regulation (GDPR) in Europe to avoid legal implications that may harm their brand image (Köchling & Wehner, 2020)

Moreover, cyber attackers find an ideal target at AI systems where candidate data is centralised. In case such data gets breached it will expose sensitive personal information thus harming those individuals affected and could make the organisation liable to significant damages. Safeguarding this information adds complexity as well as cost to implementing AI in recruitment. Moreover, the mishandling of information can cause distrust among applicants who may shy from offering personal data if it is not protected well (Ore & Sposato, 2022).

1.8.5 Over-Reliance on AI and Automation Risks

Although AI can perform routine functions such as resume screening and interview scheduling, it is not perfect. When the AI system's algorithms or data inputs are flawed, it can make wrong choices like rejecting good candidates or promoting unqualified ones (Ore & Sposato, 2022). These mistakes can have grave consequences for a firm like missing opportunities to employ the best workforce and ruining its image. Another problem with depending too much on AI is that the human recruiters' ability to think critically and exercise judgement decreases. As more recruitment tasks are taken over by AI, recruiters might become lazy believing blindly in the decisions made by AI. This could result in lack of monitoring, hence failure to identify mistakes or biases in decision-making by these machines. In some cases relying heavily on this technology may lead to underrepresentation during hiring as inadvertently AI systems will favour people who fit into certain patterns (Brishti & Javed, 2020).

1.8.6 Resistance from Employees and Candidates

A further problem may come from resistance by employees and candidates in relation to the introduction of AI during the recruitment cycle. Concerns could arise among

recruiters that AI would make them lose their jobs, which results in job insecurity and AI adoption resistance. Even though the intention of AI is not to replace but to assist human recruiters, apprehension related to AI as an imminent hazard may escalate tension hence reducing the efficiency of hiring team (Ore & Sposato, 2022).

AI-based evaluation of candidates instead of human assessment might be seen as a potential issue among applicants themselves. This can be attributed to their perception that AI lacks a personal touch and does not involve consideration for one's unique strengths or possibilities. Such disapproval can result in negative candidate experience and possible attrition of leading talents from companies that largely rely on AI during selection processes (Dijkkamp, 2019).

1.8.7 Ethical Concerns and Accountability

In this respect, there are several ethical concerns associated with using artificial intelligence in staff recruitment procedures, especially accountability challenges. Identifying responsibility for such hiring decisions becomes problematic if these determinations were made by an artificial intelligence system—whether it is a human who developed algorithms underlying such an intelligent system or an organization deploying it or is it the system itself (Prabhakar, 2023). This could be a problem if AI decisions end up being discriminatory or leading to other negative results, and in the absence of clear accountability.

Still, the moral implications of applying AI in recruiting go beyond just that. For instance, it is an ethical matter whether companies should be allowed to monitor candidates' social media profiles through AI or conduct sentiment analysis on their communications when looking for top talent. These ethical concerns need to be considered by organizations as well as develop policies that will guide the proper usage of AI in recruitment (Köchling & Wehner, 2020).

1.8.8 Technical Limitations and Integration Challenges

Despite these advancements, there are still some technical limitations that interfere with its effectiveness at recruitment. For example, this may encompass difficulties around such issues as understanding ironic statements or complex human languages and idioms like sarcasm, humor or cultural references present within the candidate's responses. Likewise, non-standard resume formats can pose problems for AI systems which may struggle with identifying transferable skills not explicitly stated in an applicant's CV (Dijkkamp, 2019). Equally challenging is the incorporation of AI systems into existing HR technologies and processes. This might require organisations to invest in new infrastructure or considerably modify their prevailing ones to be able to accommodate AI. This process of integration can be quite expensive and time-consuming, with the risk that the AI system may not perform as intended thereby disrupting the hiring procedure (Ore & Sposato, 2022).

1.8.9 Long-Term Implications and Strategic Risks

The final thing yet to be known is about long-term implications for using AI in recruitment. As AI technology advances further, there is a danger of organizations over-relying on artificial intelligence systems thus losing human expertise and judgement during recruitment. Such strategic risks include lack of diversity in hiring or inability to adjust to changing labour market conditions (Ore & Sposato, 2022). However, today's AI systems may soon become obsolete or need frequent updates to maintain usefulness as a result of rapid technological change. Organizations should therefore be ready for continuous investment in artificial intelligence technology as well as watch out for new advancements so that they do not lag behind others (Brishti & Javed, 2020).

1.9 Balancing AI and Human Touch in Human Resource Operations

To strike the perfect interaction between humans and AI in recruiting, a balance needs to be achieved between technological efficiency and human interaction. This might mean the use of AI in repetitive and data-driven activities. Still, at the same time, human recruiters should be engaged in activities that apply empathy, intuition, or personal contact. For example, it can conduct resume screening to choose the most capable candidates and leave the rest to human recruiters for interviewing and feedback. Additionally, organizations must focus on transparency and fairness in their recruitment process. It requires developing and overseeing such systems that implicate reduced bias with clear information provided to candidates about how their data is being used. By creating a transparent and fair recruitment process, organizations can have a much better chance of building trust with candidates and ensuring a positive experience. For instance, though artificial intelligence can process huge amounts of information to find common features in employee behavior patterns, only a human professional can identify reasons behind these trends as well as react adequately. Machines cannot recreate interpersonal interactions between managers and subordinates who need reassurance or advice. This makes it crucial that certain aspects like employee engagement and conflict resolution are based on individual cases (Wajid & Kellis, n.d).

1.9.1 Importance of fairness in AI based HR Practices

Ethical concerns arise when AI is integrated into HR practices with respect to fairness and transparency. Bias in the recruiting outcomes, including employment and promotions, may be due to a continued use of biased data when training AI algorithms. This potential for bias indicates that fairness should be prioritised in HR practices driven by AI systems. For instance, companies must focus on proper testing and examination of these algorithms so as to identify biases and make sure decision-making processes are transparent and explainable for all stakeholders (Wajid & Kellis, n.d.).

Also, transparency is critical in maintaining trust between employees and candidates. If the human resources department relies on artificial intelligence programs whose results are seen as arbitrary or opaque then people tend to lose faith. To address this issue organisations should adopt AI models that can provide explanations to its actions thus allowing the employees to easily seek clarifications about any decisions made using this tool (Wajid & Kellis, n.d.). The use of AI in HR can make some advantages in terms of efficiency and decision making. But it is also a major risk if the process is not properly handled. These are main worries which have to be addressed for the AI's long-term success in HR such as the potential for overdependence on AI, the perpetuation of biases, and erosion of human judgement. Organisations can strike a balance between AI and a human touch by emphasising fairness and transparency in decisions driven by artificial intelligence, enabling them to enjoy the advantages brought about by IA while still maintaining key human elements that must be present for effective HR manage

1.9.2 Best Practices for AI Integration in HR: Insights for Management and Business Leaders

Finally, this area of research will offer management and business leaders essential insights into incorporating AI into recruitment processes. It will indicate the best practices for harmonious interaction between humans and AI to ensure that recruitment is carried out effectively and humanely. Furthermore, it may provide some practical advice on mitigating risks and potential bias in the dehumanization that results from recruiting with the aid of AI. Thus, leaders and business executives in management have the challenge of learning how to use AI in the recruitment process if the organization is to maintain its competitiveness in job markets both now and in the future. In this light, only a balanced approach allows organizations to realize improvements in recruitment that will help them attract the best talent and elevate candidate experience. Therefore, this research will help

guide the implementation of AI in organizations in recruiting and provide actionable insights and recommendations to achieve optimal interactions between humans and AI. Integration of AI in recruitment has both opportunities and challenges. While AI enhances efficiency and makes the process more accurate, at the same time, it brings forth issues such as dehumanization and bias. The main objective of the research is to bring out the potential and limitations of AI in recruitment, focusing on a balanced approach that may maximize the strengths of both AI and human recruiters. In this way, it will set guidance for organizations looking forward to adopting AI in recruitment to make sure that the interaction of humans and AI is optimal.

1.9.2.1 Hybrid Approach: The Combination of AIs with Human Expertise

The most effective strategy for integrating AI into HR is adopting a hybrid approach which combines AI capabilities with human expertise. While routine tasks can be automated by an AI, large datasets can be analysed as well as patterns identified; it is important to remember that humans offer empathy, intuition and judgement – these being essential attributes when managing individuals. For example, resumes may be screened by an AI and candidates who match certain requirements identified whereas actual interviews should be carried out by people within the HR department who can also make final hiring decisions so that they can tell if the candidate fits the organisation's culture or values (Gikopoulos, 2019).

1.9.2.2 Continuous Learning and Adaptation

Rapid development in AI makes it necessary for organisations to keep on learning and adapting. In order to be updated with the latest trends of AI systems, they should be regularly changed, thus necessitating that HR practitioners are also trained on how best they can use these tools. This ongoing adaptation process ensures that AI systems continue to deliver value and HR remains competent in leveraging these tools for organisational

benefit (Wajid & Kellis, n.d.). For instance, Google constantly updates its AI systems while ensuring that comprehensive training programs are put in place for its HR staff. With this approach towards continuous learning and adaptation, Google has been at the forefront as a leader in innovative HR practices so as to ensure effectiveness and relevance of its AI tools (Gikopoulos, 2019).

1.9.2.3 Explainable AI (XAI) and Accountability

The implementation of Explainable AI (XAI) is very important in HR because it helps hold accountable decision-making processes steered by artificial intelligence. XAI systems provide clear explanations for their decisions enabling HR professionals to understand and validate these decisions before they are implemented. AI integration in HR requires ethical governance as an integral ingredient. AI ethics committees and governing bodies have been set up by organisations to ensure they use artificial intelligence properly. These frameworks make sure that the implementation of AI technologies follows Ethical Standards and any other applicable rules in place. Others include dealing with data privacy concerns and how to address biases associated with artificial intelligence-driven decisions (Wajid & Kellis, n.d.).

Microsoft's stance on AI governance demonstrates the significance of ethical oversight. The company has created an ethical advisory board for its AI to ensure this technology conforms to strict principles at all times. In terms of HR function, this governance structure is used by Microsoft to protect employee information through responsible use of AI (Gikopoulos, 2019). Among the most notable recent changes in organisational management is the inclusion of AI in HR processes. With organisations increasingly embracing AI, its potential benefits like enhanced efficiency, data-driven decision-making and automation of routine jobs are becoming clearer. However, this revolution also has intricate issues that need to be carefully thought about as well as

balanced. From recruitment to employee management, huge amounts of HR have been impacted by AI's ability to quickly and efficiently process huge volumes of data. The blended approach entails combining human expertise with artificial intelligence capabilities and is currently viewed as the most effective strategy for applying AI in HR functions. Whereas artificially intelligent systems excel at automating repetitive tasks and spotting trends within data, they fail when it comes to empathy, intuition or judgement which are critical in making refined decisions, particularly related to activities such as candidate selection and staff engagement. By working with both human input and AI simultaneously, all advantages resulting from adoption of AI may be achieved without losing such important elements contributing towards a positive workplace culture.

However, it is also important for HR to be fair and transparent when it comes to combining AI features. Such systems of AI, if not properly managed, can maintain and even intensify prevailing prejudices that result in discriminatory effects in hiring and other HR procedures. Algorithmic fairness requires the use of varied and representative datasets in training AI systems, routine audits of such systems for identifying biases and rectifying them, as well as openness regarding AI-driven decisions. Transparency is more than just a technical requirement; instead, it helps build trust among workers as well as potential employees. This encourages confidence in the organisation's HR practices because it makes sure that AI systems are transparent with decision making processes being explainable or understandable.

Moreover, as rapid advances are seen in AI technology continuous learning and adaptation cannot be underestimated. Organisations must invest continually both in the latest HR training methodologies and technology on artificial intelligence. By doing this, they allow their HR professionals to remain up-to-date with advancements in AI which consequently keeps the effectiveness of these AI systems alive while empowering them to

gain maximum benefit from using these tools for their work. The integration of AI into HR is not an isolated event but rather a process that changes over time and calls for adaptability.

To conclude, integration of AI into HR practices can significantly improve efficiency, accuracy, and fairness in managing human resources. However, these benefits can only be achieved if organisations strike a balance between AI capabilities and human expertise, ensuring fair treatment and openness to change, adopting explainable AI approach while taking into consideration ethical governance principles at all levels of operation. In this regard organisations will benefit from AI's immense potential while still preserving those aspects that make for an inclusive workplace culture. HR's future is balanced on this fine line where artificial intelligence assists man rather than replacing him. This way, it will not only improve human resources' practices but also contribute to the overall success and sustainability of the company in a world that is increasingly digital.

CHAPTER II: REVIEW OF LITERATURE

2.1 AI's impact on efficiency and challenges

The rapid development of new technologies, and especially Artificial Intelligence (AI), has undergone reform in the way the recruitment process is carried out today. Recruitment, one of the most resource-investing activities of Human Resource Management (HRM), contributed notably from the advent of AI technologies, which take away the basic non-productive processes in recruitment. However, the HR practitioner's relationship with sophisticated technologies is also affected by several tensions. Issues such as lack of transparency and fairness, rather than relying on technology – human interactions or decision-making processes which are very sensitive about cultural sensitivity and soft skills, remain critical. This literature review will provide an overview of the literature that provides evidence for the positive effects of using AI in recruitment, the negative effects associated with the use of such technology and even suggest concepts that will describe how this cloud-based system would be successfully implemented in most organisations.

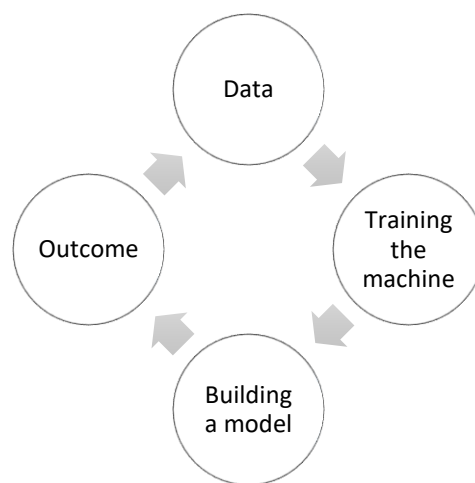


Figure 1: A simple explanation of how machine learning is developed, and outcomes are produced presented by Soleimani et al. 2021.

2.2 AI's Role in Improving Recruitment Process Objectives

2.2.1 Automation of Routine Tasks

The incorporation of Artificial Intelligence into the recruitment industry has seen a positive impact as regards the everyday and monotonous activities thanks to the self-scheduling and responding systems. Normal HR functions consist of a series of recruitment procedures commencing with the definition of a need in human resources and completion of recruitment by a hired employee.

AI-assisted Applicant Tracking Systems (ATS) have revolutionized this process by performing automated resume screening and enabling the management of a huge number of applications in a very short time (Khair et al. 2020). Pre-existing criteria employ chipped algorithms figure up resume cuts commensurate with cliches, basic apparent highlights, experience and others related to the advertisement in question. The automation of these tasks is such that HR managers, for example, can concentrate on more worthwhile activities like interviewing candidates, and assessing them for additional qualities like, for example, how well they would fit into the organizational culture, leadership potential among others. Proposition: Köchling and Wehner (2020) contend that not only does AI take over the repetitive tasks of administration, but it also enables better quality hiring as the most qualified candidates are targeted from the beginning. This leads to better optimization of HR activities in HR departments (Köchling & Wehner, 2020). Furthermore, there is a high trend of implementing AI chatbots for dealing with the initial correspondences with the candidates. These computer-based virtual assistants can help respond to the candidate's FAQs, set appointments, and even make the first rounds of appraisal with their tasks minimizing the efforts of recruitment and selection (Huang & Rust, 2018). Such businesses

can automate these interactions and respond to applicants instead of being constrained by communication and manual processes that create delays, clutter, and slow response times.

2.2.2 Predictive Analytics in Recruitment

Apart from the interfaces, AI also exhibits recruitment technology functionality by providing analytics and forecasts. This helps suggest to the employer the expected performance of the applied for candidates based on their past statistical data on hiring. This predictive capability is beneficial in improving their hiring processes as well as minimizing cases of hiring and firing employees. For example, they suggest that AI employs rational assessment of the candidates through their resumes, performance at job interviews and job performances in the previous positions in the past CVH in determining the analysis of the candidates (Khair et al., 2020). As a result, recruiting professionals will be able to rely on data rather than purely on intuition, which can often lead to blunders in terms of choosing the wrong person to fill a position because of missing some key facts.

The unique advantage of predicting analytics is its ability in finding suitable candidates who may not have followed an ordinary career. The employment of AI systems in this manner considers non-standard career paths and helps Recruiters with alternate criterion. Koen et al (2020) pointed out that that AI contributes to enhancing the vision about people and making judicious decisions which is crucial in making recruitment processes shorter and more diverse (Koen et al. 2020).

2.2.3 Larger Engagement and Varied Talent Base

AI makes it possible to go beyond such limits in seeking for applicants. Courtesy of traditional recruitment, job ads and networking are some of the common methods employed which restrict the hunt to people who are ready to accept job intentions. However, AI can scout for prospects from other online domains like social media, business networks, and job sites. Köchling and Wehner (2020) argue that to leverage AI often entails

searching several engines simultaneously which guarantees exposure to more eligible candidates which increases the pool of candidates (Köchling and Wehner 2020). This encompasses a larger reach which is essential for Companies who seek to enhance diversity and inclusion in their employment.

Geographical limitations in recruitment can be Eco systematically conquered with the application of AI technologies as companies can now search for employees in other countries. In today's, situation this ability is very desirable for companies, as the workplace is becoming more and more remote and globalized. Further, as organizations begin to accept deeper levels of remote working, the scope of AI where it can look for candidates across the world for firms will only make frontline workers' recruitment more efficient and inclusive (Goyal, 2021).

2.3 Concerns of AI in Hiring Effectiveness

2.3.1 Grey area (The “Black Box” Problem) of AI based recruitment

In recruitment, one of the main problems in AI systems' use is that there is no transparency in how decisions are taken by AI, sometimes termed as the melody of the “black box”. AI systems in general, and machine learning systems in particular, have been engineered and designed in such a way that even the engineers and the developers who make these systems cannot explicate the processes that lead up to the making of certain decisions (Khair et al, 2020). This lack of consideration becomes a great problem in recruitment where reason must be provided when rejecting or accepting candidates, especially where a machine determines something that seem outrageous for human resource suspects. Relying on AI systems' opaque nature presents problems in the use of these systems from the perspective of both recruiters and candidates. For instance, if the AI system rejects a candidate, it creates a challenge for HR personnel to defend who makes the decision and why, especially when algorithms with a hundred features are doing the

measuring. This inconsistency in understanding can pose legal threats to organizations, especially in jurisdictions where laws against opacity in hiring are intense. Potential abundance of such justifications could expose the firm to adverse effect on its reputation and litigations from other stakeholders because of the arbitrary nature of AI driven decisions (Köchling and Wehner, 2020).

2.3.2 Bias and Discrimination in AI Systems

On one hand, AI can allow for more evidence-based hiring, however, it can also reproduce or make worse existing biases if not handled properly. Ultimately, AI's effectiveness relies on the underlying data. For example, if the data contains biases in relation to gender, races or socioeconomics, then the biases will become apparent in the AI's decision-making. For example, if an AI is trained on past hiring data, this will bias the AI not to hire women for technical positions since past hiring patterns showcased a bias to hiring men for those positions. Khair et al. (2020) contend that these systems will not improve the propensity for racial bias due to the reason that they are trained using historical data which is often biased towards particular ethnicities. In other words, AI harvesting tools that look at the hiring patterns of the past might continue the same traditions, such as recruiting from the over-represented educational or geographical areas in the company or getting people of certain races. This bias can be particularly negative in the context of diversity and inclusion initiatives since it can prevent hiring of minorities (Khair et al., 2020). Furthermore, alternatives affecting such candidates are inadequate because effective recruitment may involve the use of AIs that have an element of pattern recognition. Even this is alarming foresight especially when trying to assess soft skills or even someone's cultural fit, which is often very important in predicting a candidate's performance yet very challenging to gauge accurately by machine learning. They may also be evaluated poorly

by AI systems where the path of conventional metrics hierarchies is prioritized due to the enactment of such non-conventional career paths (Huang and Rust, 2018).

2.3.3 Inability to Assess Soft Skills

Topping the list of the most pronounced disadvantages of AI in recruitment is its inability to evaluate soft skills properly—that is qualities such as creativity, emotional intelligence, leadership ability, and fit for the organisation. Engineers are able to analyse reports of facts such as educational achievements and work experience; however, they have to deal with intangible qualities of the people they hire which are usually imperative as well. Team members like Khair et al. (2020) explain these elaborate ‘coverage gaps’ by say that although kahir is best suited for employment screening his AI system will identify candidates with relevant technical skills but not the capacity for such harmony, exhibit professionalism and support change.

One goes further to demonstrate how this can lead to disturbing hiring practices. An example is an individual who has good qualifications that are purely technical but has low emotional intelligence with regards to leadership: such an individual is more likely to be selected by the AI even when there are better candidates with good interpersonal relations. As a result, this presents a huge problem in recruitment where leadership and client management roles are largely reliant on both technical and non-technical abilities. Regardless of these difficulties, those in favour of AI within recruitment believe that AI will help decrease human biases and enhance accuracy in further hiring processes. Recruiters themselves are known to be influenced by several biases, it could be the performer’s name, appearance, gender or even ethnicity that may guide their choices. When used properly, AI systems can also reduce these biases by being targeted towards data and eliminating psychological aspects that are prone to being subjective (Davenport and Ronanki, 2018). For instance, AI can mask the applicant's name, contacts and even photos;

therefore, the recruiter is less likely to be confused by some typical aspects, instead concentrating on the necessary skills of the candidate (Huang and Rust, 2018). AI has this opportunity in the context of hiring advanced and capable candidates, that is a prerequisite for discrimination free hiring. Also, the AI systems could be designed to enhance diversity by informing managers about some important missing criteria in the head hunting and providing them with candidates who are really different. According to Goyal (2021), although there are concerns around the ethical use of AI, it can be employed by organisations as an aid to meet diversity and inclusion to a degree of flagging certain instances in which the hiring processes may create inadvertent bias against minorities. When applied appropriately, artificial intelligence can assist companies in enhancing the team's overall composition by implementing an improved approach towards hiring (Goyal, 2021).

2.3.4 Recruiter's Image and The Role of Artificial Intelligence in Recruitment

There is abundant evidence regarding the benefits of adopting AI, and this where the technology achieves dramatic efficiencies, however it is evident that there is a human component which is critical in recruitment endeavours, especially when it comes to areas that contribute to the core activities of any organisation such as emotions, intuitive judgment, ethical issues and so on. It was established by Bankins et al. (2022) that there is an inclination among candidates and employees that when a decision is to be made, it should be done by a recruiter rather than an AI system, and especially in such instances where the decision calls for a rejection. Human recruiters provide context when giving feedback that remains underreported – something that sits well with AI's limitations (Bankins et al., 2022).

In recruitment, decisions have considerable ramifications on the individuals' careers and life and therefore an attempt to Reengineer recruitment through Reliance on AI

should be accompanied by Human judgement & Experience. Some processes in the recruitment lifecycle especially at screening levels are better positioned to be performed with the help of AI than traditional methods to minimize time lost doing them. Screening & candidate sources can be achieved with AI & rest including interviews, final decisions etc to be done purely by human recruiters. This human-AI collaboration guarantees the efficient execution of recruitment processes as well as upholding the feelings and understanding that human- individuals are attuned to (Huang and Rust, 2018) on the other hand.

However, this approach is not always feasible and proposes a full use of what AI can offer in recruitment while searching for ways to overcome its drawbacks. They should seek to advance and utilize XAI because these artificial intelligence systems will help harm sensitive recruitment processes by replacing them with more efficient systems. Davenport & Ronaki (2018) note that to enhance the employment of XAI throughout the recruitment process, organisations could employ XAI systems which encourage the AI decision-making paradigm in employee recruiting through enhancement of trust in AI. In these cases, periodical audits of the AI systems become crucial in identifying and rectifying any biases that develop over time. Köchling and Wehner (2020) further advocate for regret calibration for every enforcement that targets commercially sensitive data and the criticism for bias, monitoring the data being used to train the psychotypes so that they do not cause any adverse impact in risk management practices (Köchling and Wehner, 2020). This is most relevant to organizations looking to increase the success of the hiring authorities by increasing the diversity and inclusion in the hiring processes.

While AI can efficiently handle many aspects of the recruitment process, human recruiters should remain involved in the final decision-making processes. In today's battles, justified as benevolent, organizations neither forget about nor ignore AI's predilection to

impose bias on complex issues, ‘Thanks to AI, these approaches will allow us to evaluate the candidates in a more empathetic way’ (Khair et al., 2020).

In harsh realities of “Deep State” and subpar democracy, understanding the differences and inherent biases in decision-making finally paid off. Although the benefits of the increased efficiency in respect to AI-powered hiring are unquestionable, the discussion subsequently leads to ethical principles and fairness issues, which are recognized as hot topics of scrutiny in this digital era. The burgeoning integrative use of AI in these preparatory even hiring and selection decision-making processes primarily raises moral concerns about the impact all those personal information or behavior systems can have on the people that are subjected to all those control warnings.

These worrying features raise questions of fairness in the use of AI in recruitment. These include bias, accountability, and transparency. While AI technology is praised for saving time and eliminating mistakes in procedures, it is well known that most AI systems learn based on existing data which may make discrimination deeper, particularly against stigmatized members of society. In relation to this Khair et al., (2020) note that, biased data sets are a great contribution to AI brains. While the brains are developing algorithms for recruitment, some groups may be left out. This negates equity and brings about great ethical issues in regard to non-discriminatory practices and equal opportunities in recruitment processes (Khair et al. 2020).

Furthermore, besides bias, many AI systems’ operations raise questions about clarity because of their “black box” characteristic. AI says that as it was explained in the previous chapter, many of its judgment and decision-making results are conveyed without much context as to why certain decisions were made. When such contexts are negative, it renders the AI as arbitrary, which raises a lot of concerns on the issues of accountability as well as transparency in recruitment process for ethics should be maintained. Köchling and

Wehner (2020) asserted that people should be in position to account for their actions, particularly when a decision fostered is supported by a candidate and such has adverse effects on the individual's employment opportunities (Köchling and Wehner, 2020). Not being able to explain the logic articulation behind something as complex as an AI-based decision may erode the mainstream support which in turn complicates the ethics of recruitment.

Further, fairness in AI recruitment is not only about eliminating bias; it also means avoiding the mechanization of the recruitment process due to the adoption of AI. It is well acknowledged within the literature that AI is effective in executing dull and routine tasks, however, it performs poorly in evaluating soft attributes like creativity, emotional intelligence, and cultural fit. Those qualities are critical for determining the chances of an individual being a productive employee in the long run, but are hard to estimate with the help of AI tools. If recruitment decisions are based on the premise of employing the use of data, then, there are implications that although the hiring decisions may be optimal, they may not be equitable, complete, as they hasten to exclude some of the critical areas concerning people's attributes. Bankins et al. (2022) ranked empathy given by recommendation AI the lowest and perceived negative decisions made by AI to be the least fair as compared to humans (Bankins et al., 2022). This suggests that despite the increasing constraints that AI technology may impose on hiring, some degree of human judgement remains necessary for ethical engagement when AI tools in recruitment are applied.

Thus, bridging the efficiency-focused literature review with the issue of ethical considerations and fairness, it is evident that while AI has a lot to offer in terms of recruitment, there are still ethical concerns that ought to be addressed. The aim is to capitalize on the strengths of AI while eradicating its weaknesses especially in relation to biases, transparency, and the eradication of humanity in making decisions. In this

connection, AI systems and human recruiters can be integrated in a way that recruitment will be efficient but at the same time ethical and just as well conducive to the social goals underlying the policies of equity and justice. The development and implementation of ethical principles and guidelines that would prevent manipulation or corruption of AI recruitment systems, protection of rights, and ongoing control of algorithms are critical to ensuring reinforcement rather than deterioration of ethics in recruitment when applying AI.

2.4 Ethical considerations and fairness

The adoption of artificial intelligence (AI) in the hiring framework is one of the areas that has witnessed allot of interest owing to its presumed capacity to make the processes more efficient and objective. On the other hand, many people are thrilled by this development until a plethora of literature emerges that raises ethical issues on the use of AI in recruitment particularly on fairness, transparency, bias and dehumanization of recruitment processes. The comfort and efficiency that AI technologies hold out to recruitment processes on the likelihood of cutting back on human errors raises ethical issues relating to the design of such systems and the effects such systems have on people and organizations. This literature review aims at understanding the ethical dimensions of AI use in recruitment with a particular emphasis on fairness, bias, transparency, and agency of humans over the decisions being made.

2.4.1 Dehumanization in AI Recruitment

Discrimination & AI HR Management Given That AI Replaces Humans & Insensitive Mgmt & Unfair Placement Of Technology Humans Ability Where the preemployed recruits Also Fall Out. One of the most controversial issues associated with the usage of AI in recruitment is that it will lead to the dehumanization of the recruitment process. Dehumanization in this case refers to the process of taking people away from the equation including their sentiments and human relations in administration, which leads to

thewendung; a requisition process which resolutely emphasizes efficiency and margins of hiring over human relationships.

Fritts and Cabrera (2022) stress that the implementation of AI systems in hiring could also lead to ‘dehumanization’ since crucial stages of decision making become devoid of human presence. They further assert that such processes will leave a feeling of alienation among the candidates because of the nonhuman interaction in the process as incorporation of AI’s self-defined mechanisms into a human recruitment system is not possible. Fritts and Cabrera (2022) further elaborate that in addition to such forms of values, the concern of dehumanization becomes worse considering that such AI recruitment systems tend to embed ‘artificial values’ in their structures. It is easy to programme these artificial values into the algorithm, but they do not correspond with the integrative values that are exercised by human recruiters. For instance, interpersonal or communication or enthusiasm, or cultural assimilation while recruiting which cannot be measured easily by objective indices. However, AI does the opposite by compressing job applicants into a delineated measurement which may lessen the appreciation and knowing of the person being hired. This is dangerous in scenarios like employer and employee relations where social ties and trust must be maintained (Fritts & Cabrera, 2022).

In the review of the “gamification” way of communicating, Nguyen (2021) provides valuable information as to how this recruitment practice is dehumanized by AI. For example, Nguyen, holds that AI systems like Twitter with their gamification of communication create false simplification of complicated concepts such as human values. This results in a situation where the contextual interaction is replaced by the interaction metrics (e.g. likes and retweet or in the case of AI recruitment, scoring, or ranking) which are commercial in value. This is relevant to in – AI recruitment as it depicts how algorithmic engagements can pervert humanity by reducing the evaluative criteria to the

simplest metric possible. Human recruiters may defer when it comes to making subjective calls but being able to deal with the emotional aspect of it, which in this case are people, is a very critical point in the recruitment process that can be difficult for AI systems to perform (Nguyen, 2021).

2.4.2 Fairness and Bias in AI Recruitment

An important ethical issue in AI recruitment concerns fairness and this includes biases that may originate from the very algorithms that will be employed here. The advantage of AI systems is that they are viewed to be unbiased and free of any prejudice therein accentuating a wrong bias which humankind tends to possess towards decision making. It is a well-documented fact, however, that AI systems are biased or can cause bias, particularly when the training data mirrors societal bias or stereotyping.

Drage and Mackereth (2022) are particularly critical of the marketing strategies of AI recruitment companies that argue their systems remove race and gender and thus objectively evaluate candidates. They contend that the assumptions underpinning such claims are wrong in the first instance as they do not appreciate the character of race and gender as forms of power, but as specific and disjointed characteristics. The belief that AI can 'remove' race and gender- 'attribute' bias in the employment process ignores the wider environments within which these systems operate. It is not that problem solving AI systems will eliminate discrimination. There is danger in this logic that AIs will in fact be used but will be biased unless the members of society abandon the very things that Kuo et al (2022) seek to rectify with AI.

A popular instance of bias in AI-aided recruitment is said to be the AI recruitment tool that Amazon adopted for hiring activities and which proved gender biased with female applications favoured less than male applications (Dastin, 2018). In the event, the algorithm was trained on historical data driven on the stereotypical male-dominated nature of

Amazon's employees. So, the Algorithm was biased towards male candidates because that had been the trend in previous hiring at such an A.I company. Drage and Mackereth (2022) assess that such cases illustrate the dangers of applying AI without fixing the biases in the training set especially in the case where the AI is recruited. Artificial intelligence (AI) systems cannot be perverted against any ethnicity since all said systems depend on trained data. And when such data is historical the bias will always be there (Drage und Mackereth, 2022).

In addition to gender, race also emerges as a critical barrier in the use of AI-enabled recruitment. Noble (2018) illustrates how systems that are informed by historical data introduce biases that disfavour certain groups, in particular, the most disadvantaged ones. Quite often these systems simply reproduce the stereotypes and the discrimination that barriers their data from wider society profoundly. In such premises it is necessary to underline that there are reasons which may broach and even worsen the overall tendency of discrimination while hiring personnel. For instance, sourcing policies that promote certain kinds of schools or some work experience may have exclusionary effects on candidates from certain races and socioeconomic standpoints (Noble, 2018).

The views of Binns (2018) are focused on the problem solution, seriously criticising segregation of the fairness evaluation of an AI system from its surrounding society, clarifying that, fairness is relative to social context. The fact that AI could end up legitimizing the distorted view of social hierarchies already in existence implies that there is a need for these systems to be critically engaged with at all stages to prevent misevaluating. Binns (2018) stresses that as Artificial Intelligence (AI) technologies get implemented, systems of fairness audits and accountability must be included in order to achieve ethical results in recruitment and other similarly important activities. The second important ethical issue has to do with the Introduction of AI in recruitment systems.

Transparency and accountability are yet additional problems which are raised in the category of artificial intelligence systems deployed for recruitment. A decision made in the matter by AI systems is known not to be disappointing because candidates and even employers are probably in darkness, how that conclusion came to be, which is a task. The problem with lack of transparency is that trust in the recruitment process declines and even questions of who is accountable to whom come into play.

It is noted by Fritts and Cabrera (2022) that suitable measures on AI recruitment should include nervousness by candidates concerning many decisions made in the recruitment process because of the encouragement by the information provided in AI. Without worrying, candidates will just ignore processes that they feel understanding is absent, and they will be unable to challenge actions taken that they view as wrong even when upper management cannot comprehend the reason for the movement's delay.

Do such opaque AIs raise ethical issues such as attempting to shift blame? In cases there is need to use AI systems for hiring, when a problem occurs or arises, it is not clear who should be held responsible. If Aishat is biased against a candidate during hiring and uses an AI algorithm to make that unfair conclusion, who gets the blame? Is it the institution that created the AI system, the organization that made use of the AI system, or the software engineers that built the AI program? The more the power of decision making is decentralized, the worse the problem of solving the ethical issues posed by such systems.

Drage and Mackereth (2022) note that AI recruitment systems are opaque in that they over-reliance on predetermined algorithms, resulting in biases being buried further into the systems. And in the same way, AI systems that are deployed to eliminate biases in decision making, contradictory problems are presented. Also called as “black box” algorithms, which are algorithms that cannot nor are allowed access to the users inner working of the algorithm or understanding of the scope of the function that the algorithm

or the predicted model carries out, add to the undoing of achieving fairness and the accountability of AI recruiting (Drage & Mackereth, 2022).

Lack of transparency is why Pasquale (2015) has critiqued the increasing emergence of the “black box” algorithms even when they are employed in efforts that are bordering at high risk such as recruitment. For example, in the contexts of recruitment, AI recruitment systems which employ non-readable or non-opaque algorithms are either unjustifiably biased or unjustifiably penalize some candidates without any means of explaining how these are arrived at. This opacity not only erodes confidence in the processes but also hampers the capacity to appeal against actions or rectify mistakes (Pasquale, 2015).

2.4.3 Power Relations Embedded in the AI Recruitment Process

In addition to issues of transparency and accountability, Drage W. & Mackereth J. (2022) also identify power relations that are embedded within these AI recruitment processes. Such systems compel applicants to assume a more passive position whereby they are argumentatively evaluated by underlying artificial intelligence algorithms created and managed by a third party. This creates an asymmetry between the “observer” (the AI system) and the “observed” (the candidate). The former remains in charge of decisions to be made concerning the latter’s suitability for a specific role. This power dynamic is especially dangerous because historical data regarding hiring practices, which is often the basis for AI systems, perpetuates existing structures and injuries.

In the opinion of Drage and Mackereth, AI systems are certainly more than mere attribute identifiers; they also perform the work of determining who best fits the profile created through the embedded criteria within the algorithm. This is to say that the AI systems are not just those systems looking over the world; rather they also degenerate the social structures by enabling the reinforcement of the relationships and structures of power. Importing subjective viewpoints and layering pre-built structures, reinforcing the status

quo also comes as a consequence to the use of AI systems for the recruitment of the ‘ideal candidate’ (Drage & Mackereth, 2022).

Eubanks (2018) points out that all AI technologies, used outside of analytical or engineering settings— and in this sense most especially in recruitment— does not simply function as a tool but is self-contained within certain political spheres which have historically oppressed certain minorities. Because of this embedding of structural inequalities in AI technology themselves, they will tend to perpetuate structural inequalities by biased evaluations and decision-making that unduly relieve unacknowledged groups of people from blame. It is therefore necessary to consider the impact of AI in hiring with respect to its ethical implications especially in examining the structures of power in the context of recruiting and why certain agents decide which possible candidates are acceptable in the recruiting processes. Therefore, as AI systems are increasingly used in recruitment process, it is worth analysing how those systems define success and how they can also aid the exclusion of certain groups of people in the workforce.

Firstly, there are both pros and cons of using AI in recruitment process. On the one hand, AI systems provide the much needed speed and reduction of resource waste, but these benefits come with too many ethical implications especially on the issues of fairness and biases, lack of transparency and the portrayal the process of decision making, on behalf of humans, as one that does not require human judgement. The literature highlights that AI recruitment systems are not as neutral or objective as they are often claimed to be. Rather, these systems are constrained within the parameters of the information that is fed to the system for exposure, and when that information is intergrated with discrimination and social issues, AI systems can quite easily mimic and cause extension on them. Additionally, if AI systems may confuse candidates and employers as to what decision-making processes were employed to make which people vague on the issues of responsibility and

accountability. Last but not the least, the basic hierarchies that these AI recruitment systems exhibit also poses ethical issues in terms of who gets to be a possibly hired, as there might be established parameters that restrict the engagement of the underprivileged population.

In addressing these legal and ethical issues, it is important to create both legal and ethical solutions which are equitable, transparent and accountable for AI hiring. All parties concerned must continuously undertake in the evaluation and surveillance of AI systems for the betterment of social values like fairness and justice. This enables positive utilization of AI by organizations-controlled or limited concerning its ethical dilemmas.

2.5 Bias and Discrimination in AI and Recruitment

Discrimination against certain groups should be classed undesirable and entirely eradicated which has become humanly possible. Yet, in the age of big data, we still see discriminatory practices by automated systems. Simply put, what has been known as “machine learning”, is a set of data that is fed into a software to achieve prescribed goals (Davenport & Kalakota, 2019). When faced with an alien environment, AI draws on these data sets to achieve optimum results. Based on the yielded results, machine learning systems refine their abilities and performance. However, scholars like Schuller (2017) argue, particularly within the discipline of International Humanitarian Law surrounding use of machine learning in weaponry. Despite high advancements in machine learning and artificial intelligence, many a times, drones are unable to identify the target and instead hit civilians that may have shared some features (like wearing a turban, having a beard, certain clothing) with the original target. This inability to discriminate has caught a lot of world’s attention on how AI and machine learning can be improved to avoid such drastic mistakes especially in areas of high risk to civilians. Similarly, although artificial intelligence technologies are designed to have human-like abilities, cognitive thinking is not AI’s forte.

Unlike any mathematical equation that derives from a specific mathematical equation or model, machine learning is a non-traditional, non-parametric system in which data dictates how information in input variables is situated to forecast the outcome of an output variable (Coglianese & Lehr, 2017). This makes machine learning an advanced, and quick learning system which adapts and fine tunes when supplemented with new data. In the past, machine learning techniques were not easily accessible to everyone because of their high costs and expensive algorithm, computers today have the capability to adapt to these technologies at a low cost. From big companies like Amazon, Meta, Apple and Google, to small-scale startups, machine learning is now helping companies cut costs and make their processes more streamlined while producing impactful forecasts for the companies (Packin & Lev-Aretz, 2018). A prime example is that of Google when in 2017, CEO Sundar Pichai announced that Google would become an “AI-first company”, while Amazon uses AI to detect malware and strengthen cybersecurity, and Nvidia uses AI to detect future threats (DeTar, 2017).

Similarly, we can find machine learning and AI application in financial technology to detect money laundering, trade frauds, to help investors make better and refined decisions, managing hedge funds and much more (Packin & Lev-Aretz 2018), for example, Sentient Technologies Inc., has trained its AI for a decade to take global trading trends and trade stocks (Satariano, 2017). Additionally, within the field of healthcare, AI is used to manage medical records for millions of patients, preparing a diagnosis and treatment plan (Davenport & Kalakota, 2019), and to predict onset of deadly medical conditions such as breast cancer and brain tumour. In healthcare, many hospitals and research centres are making efforts to polish AI to become more ethical for example, Cleveland Clinic has partnered with Meta and IBM to “accelerate and enhance the ethical use of AI in medical research and patient care” (Cleveland Clinic, 2024).

Though AI and machine learning have made leaps in technological advancement and made deep contributions to streamlining activities across all industries, they pose multiple ethical challenges. In the recruitment industry, it is important to highlight that hiring decisions have grave consequences for applicants, defining their lifestyles and how much they would potentially earn (Raghavan et al., 2019). Packin and Lev-Aretz (2018) argue that AI is inherently biased and inaccurate and risks enabling social injustices by regulating discrimination. Internet sources are prone to data cleaning processes which raises the question of subjectivity of available data, especially data available on social media. This is also extended to data mining. Data that is mined and analysed could be based on presumptions of previous decision-makers or reflect the prevalent prejudices that occur in society. Barocos and Selbst (2016) present a deep dive into anti discriminatory laws in the US, and how data mining could be labelled inherently biased- “data mining attempts to attempts to locate statistical relationships in a dataset” by looking at patterns and regularities, data mining determines relationships which are called “models”, which are then used to automate classification of individuals and activities, and forecasting outcomes (a good example is systems detecting credit fraud, spam etc, based on correlated data). Baracos and Selbst (2016) further discuss the big data’s “Disparate Impact” especially in employment processes-

“Disparate treatment recognizes liability for both explicit formal classification and intentional discrimination. Formal discrimination, in which membership in a protected class is used as an input to the model, corresponds to an employer classifying employees or potential hires according to membership in a protected class and differentiating them on that basis..... Even if membership in a protected class were specified as an input, the eventual model that emerges could see it as the least significant feature. In that case, there would be no discriminatory effect, but there would be a disparate treatment violation,

because considering membership in a protected class as a potential proxy is a legal classificatory harm in itself.”

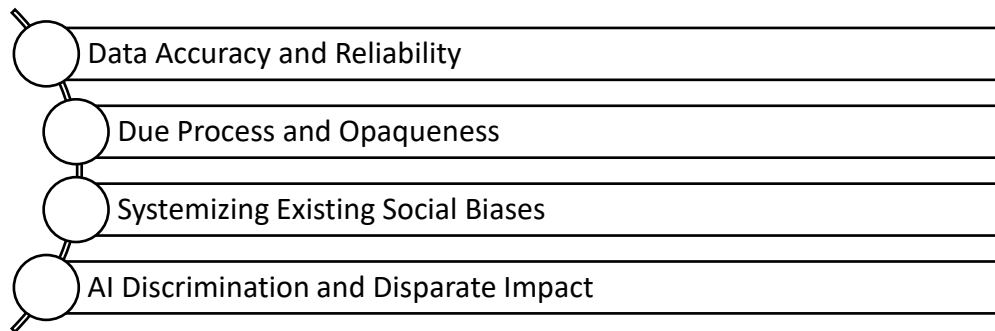


Figure 2: Ethical Challenges Posed by Artificial Intelligence (Packin & Lev-Aretz, 2018).

Further, despite the data mining and automated processes having a life altering ability especially when it comes to employment, the processes are kept opaque (Bracha & Pasquale, 2008)- meaning that for the normal person with minimal or no knowledge of automation and data mining, it is very complex to comprehend algorithmic predictions. This level of opacity is troubling when it comes to accountability of biased and discriminatory practices. One reason why companies choose not to be transparent is because disclosing technicalities of information gathering could lead to push back from public and disapproval (Packin & Lev-Aretz, 2018).

Once these biases are established, algorithms systemically work on solidifying such pre-existing social biases. For example, in the United States, zip codes are much more than providing an address to a person’s location- they are also indicators of an area’s average income per household, population by ethnicity and race, age groups- which are then applied to discriminatory algorithmic designs. In the future, where we cannot remove algorithms from our decision-making, it is significant to identify nuanced variables like zip codes that hide social biases and deeply impact human judgment. It is crucial and central in the

upcoming technological advancements that we focus on variables that don't cloud our judgement. Winner (1980) argues that, "In controversies about technology and society, there is no idea more provocative than the notion that technical things have political qualities", the claim that our focus should only on be the effectiveness of technology or their negative effects on the environment, "but also for the ways in which they can embody specific forms of power and authority" which he suggests "deserves explicit attention". For example, for a very long time, mobile and web applications have been designed while not keeping in mind people with disabilities such as hearing, sight, or speech impediments, people who are handicapped, while also extending to people who cannot speak, read or write English, systemically disabling them from accessing applications, and also in the past, women. Experts of user interface and user experience design are now focusing on making technology accessible to all, or as Google iterates on "user-friendliness".

Similarly, in a Reuters report, Dastin (2018) uncovers the reasons behind why Amazon scrapped of an AI recruiting tool based on its bias against women in the hiring process. According to the report, "Amazon's computer models were trained to vet applicants by observing patterns in resumes submitted to the company over a 10-year period. Most came from men, a reflection of male dominance across the tech industry" ... which meant for the Amazon's system to prefer men over women, ignoring resumes that included the word "women", and verbs such as "captured" and "executed" which are most found in resumes of male engineers. This report offers as an example on the limitations of machine learning, and secondly, that gender bias is deeply rooted in our decision-making systems, hence, it is tough to remove them from technological advancements. Additionally, to biased recruitment practices by HR, it is also important to highlight that there is a "diversity crisis in the AI industry" overall (West et al., 2019). According to another study done by Wired's Tom Simonite and Montreal AI (2018), only 12% of machine learning

researchers are women, at Google technical roles only have 21% females, only 10% working on machine intelligence, whereas at Facebook women only fill up 22% technical worker of which only 15% are working on the AI research team. According a 2021 report (Young et al., 2021), globally, women make up around 26% of workers in Artificial Intelligence and data roles, women in AI have higher attrition rates than men, women have higher formal education than men across all industries, and across online global data science platforms like DS Central/Open ML/ Kaggle, women only comprise 17% of participants. Furthermore, bias and discrimination against women is a systemic problem as seen even in big tech companies like Google, Apple, and Tesla. According to a lawsuit filed against Tesla Inc. by six women in 2021, it was revealed that Tesla subjects its female employees to “nightmarish” sexual harassment at the main factory in Fremont, California, while higher ups turned a blind eye to complaints (Stempel, 2021). Tesla has also been sued for racial profiling in the past (Wiessner, 2021). Tesla also requires employees to sign “arbitration agreements, keeping workplace disputes out of court” (Stempel, 2021). Similarly, in 2022, 46 lawsuits were filed against Tesla by current and former employees for workplace harassment (Kay & Cain, 2022). Similarly, Google, one of the largest and leading automation pioneers in the tech industry, paid \$118 million to settle gender pay discrimination lawsuit which was launched in 2017 (Dent, 2022). Google employees also demonstrated a mass walk out in 2018, in different cities around the world, against poor handling of sexual misconduct by top executives (Carville, 2018). Additionally, Google was sued to pay a senior female executive \$1 million for discrimination, with an additional \$150,000 for pain and suffering (Wang, 2023). Furthermore, in May of 2024, two Apple female employees proposed a class action for paying women less than their male counterparts for the same work- one female employee stated that her male counterpart was getting paid at least \$10,000 extra for the same work and same hours, while also being

subjected to work with a co-worker who sexually harassed her (Maruf, 2024). Lastly, after battling in court for seven years, Oracle, a software giant, only paid two months' pay check worth of settlement to its 4000 female employees (Steinberg, 2024). Peng et al. (2019) three reasons why gender discrimination in hiring- 1) the world distribution system with certain professions hiring more men than women, 2) algorithmic bias, and 3) decision-making of humans.

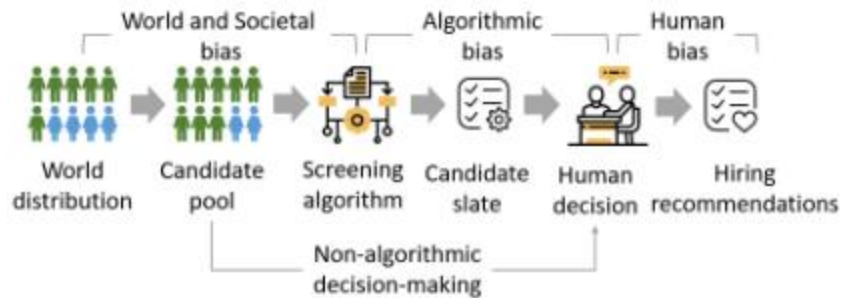


Figure 3: A schematic hybrid system for hiring suggested by Peng et al. (2019).

(West et al. (2019) suggest that we need to conduct careful analysis of AI and machine learning's ability to amplify systems of classification which are further being naturalized by these systems using big data. They also suggest and analysis of how companies are integrating this information into their decision making processes in which a special focus is placed on gender and race as categories within which "humans think about and organize their social activity, rather than a natural consequence of difference.....we need to ask: who is harmed, who benefits, who gets to decide" (West et al., 2019). Further, Houser (2019) suggests that integrating AI into decisions surrounding employment, unconscious bias can be mitigated from human decision-making. On the contrary, Houser suggests that the reason for discriminatory practices in AI are not software, machine learning, data mining, or Big Data- but humans. Instead, Houser argues that "responsible AI will abate the problems caused by unconscious biases and noise (inconsistency of

decisions) in human decision-making, and in doing so increase the hiring, promotion, and retention of women in the tech industry”. Houser (2019) further writes about how AI can help solve the diversity issues, discussed in Table 2.

Table 3 Use of AI to resolve diversity problem in recruitment (Houser, 2019).

Problem	Solution
Mitigating Unconscious Bias	- Using algorithms to remove questions of gender, race, ethnicity from initial evaluation (for example, Unbias.io which is a Google Chrome extension that removes faces/names from LinkedIn profiles) (Leong, 2017). - Blind hiring increases the chances for women to be employed (Miller, 2016). - Structured interviews against a comprehensive checklist rather than candidate attributes (McDaniel et al., 1994). - Engaging in neuroscience games such as offered by Pymetrics which creates an algorithm to match candidates with job descriptions (Pymetrics, 2024). - AI can be used to reduce turnover through practices such as tracking employee satisfaction scores. - AI can be used to manage progress of managers, such as, scanning employee reviews to detect bias, and also detect bias in job descriptions.

Reducing Variability in Decisions	- An algorithm will always provide the same decision for the same data set. - AI can do better risk assessment because AI is “noise-free” (sticks to decisions for similar inputs as compared to humans) - Utilizing chatbots in to conduct interviews. Chatbot asks the same set of questions from each candidate. - Setting criteria for promotions using an algorithm to reduce management’s bias and favoritism.
Reducing Algorithmic Bias	- Potential utility of data mining to generate new knowledge to improve decision making - By creating balanced data sets where AI is trained responsibly- “To create a balanced data set, developers duplicate the results from the less frequent category, called boosting. Developers also discard the results of the more frequent category, called reduction. They can also combine boosting and reduction to obtain more balanced results” (Houser, 2019). - Drastically increasing the diversity of data points reviewed than those conventionally considered. For example, “fairness tool” by Accenture evaluates false positives and negatives and showcase the impact they have on the model’s accuracy (Accenture, 2024). - To avoid bias amongst programmers, it is important to have a diverse team so that

consistent and just employment decisions are made.

- The “black box” issue can be resolved through providing greater transparency using processes such as “Quantitative Input Influence” (Houser, 2019) which assists in identifying reasons behind algorithmic outcomes.
-

Todolí-Signes (2019) discusses the ease of access that recruiters and HR enjoy now to information on potential candidates, while a few years ago, information was gathered solely through interviews, resumes submitted by candidates, customer evaluations, today, data is available through platforms like LinkedIn and Facebook. Big data and AI have reduced the costs for attaining information. Therefore, Todolí-Signes (2019) suggests that the use of automated systems has significantly changed “1) how information is collected and from which sources; 2) how that information is processed; and 3) how decisions are made”. Drawing on the European Union’s General Data Protection Regulation (GDPR) which has lack of specific protections for employees, Todolí-Signes (2019) concludes that there is a “need for collective governance of workplace data protection, requiring the participation of workers’ representatives in establishing safeguards”. In the case of mitigating gender bias in hiring processes, there are three key takeaways from the work of Peng et al. (2019)- firstly, a gender balanced candidate slate would ignore world distributions, however secondly, in professions like OBGYN and child caregivers there is an over-representation of women which means that “persistent preferences” cannot be changed in respects to some profession. And lastly, across some professions, the risk of having personal biases among management cannot be avoided.

In the research study done by Raveendra et al., (2020), the study questions the imminent dynamic landscape of recruitment, the prominence that the rising role of AI holds and discusses whether AI can help mitigate unconscious bias from recruitment processes. First, the paper outlines some of the common forms of biases present in the HR industry and secondly, the paper discusses how AI can be used to mitigate or minimize these biases (See Table 2). The paper concludes that AI offers potential solutions that can either minimize or completely eliminate unconscious bias and discriminatory practices from recruitment industry.

Table 4

Raveendra et al.'s (2020) suggestions for mitigating biases in HR recruitment.

Type of Bias	Role of AI
Halo Effect- selecting or rejecting candidates on the basis of singular traits, overlooking other traits objectively.	AI can be utilized to have an integrated approach which can then consider all traits equally.
Recency Bias- Only focusing on recent interview, answers, or performance.	Instead of focusing on the most recent interaction with the candidate, AI chatbots and other psychometric tools can be utilized to consider the sum of all candidate performances.
Similarity Attraction Bias and Confirmation Bias- Only focusing on traits that may be similar to that of the evaluator, and also only focusing on answers that match with the beliefs of the person evaluating.	AI considers all traits, responses and interviews equally.
Contrast- Bias that rises from differentiating between two or more	AI has the ability to choose candidates that best suit the job description.

candidates who have performed drastically different than each other. The expectations from candidates are based off the performance of a candidate who has done really well.

Discrimination between insider and AI software can be used to hide identity of outsider- The bias towards hiring a the candidates. AI also does not have the candidate who is already part of the emotional intelligence of a human. company rather than bringing a new hire.

Further, Fritts and Cabrera (2021) discuss the effects of AI on employer-employee relations. First, after a deep investigation of past literature, the paper identifies a definition for the term “dehumanization”- “removing the human presence from some process or domain” as compared to the interdisciplinary definition that simple states “conceiving other humans as lesser humans or sub-humans, or both”. Fritts and Cabrera (2019) further investigate the ways in which dehumanization occurs in recruitment processes, they identify a few ways- firstly through gamification and artificial value creation, using advanced AI technology has created artificial values in interpersonal communication. A good example is X (formerly called Twitter) where the value of a conversation is connected to the number of likes, retweets and quote tweets. This leaves less room for complex and multifaceted values. Hence, the goal is no longer to have meaningful conversations but to maximize engagements on the tweets. Just how games are designed by someone who decides the plot, designs the characters and the environment, sets goals to be achieved in a game, our experiences online are highly gamified, and hence, our online experiences are a product of someone else’s design. When gamification algorithms are extended to recruitment and selection, the algorithms choose a candidate based on the values that are fed into it. The outcomes are quantified by a programmer, however, not equal to human

values. The feedback a candidate would likely receive from an algorithm is not equal to a thoughtful conversation with another human. This is truer today than before especially in a post-COVID environment where employees get to work from home (Colaner, 2020; McKendrick, 2021).

To update and consolidate the establishment for imminent research, Hunkenschroer and Luetge (2022) methodically assess the existing literature on the ethicality of AI-enabled recruiting to date. They classify 51 articles dealing with the topic, which they synthesize by charting the ethical prospects, dangers, and uncertainties, as well as the projected methods to alleviate ethical threats in practice. Based on this literature review, the study identifies gaps in the existent literature and point out ethical questions that call for insightful investigation in future research. They make four main observations from their extant literature review: 1) they identified that of the 51 articles assessed, only three articles identify a lack of theoretical understanding of this field. Majority of the articles rather focus on legal, practical, technical and descriptive aspects of ethical considerations in the utility of AI. 2) Most research focuses on human and algorithmic bias but does not focus on accountability of the companies that employ these AI applications—this issue generates a responsibility gap. 3) The ethical risk mitigation solutions are generic and not particularly tailored to the HR recruitment and selection industry. And lastly, 4) there is a prevalence of non-empirical work. As Chamorro-Premuzic et al., (2016) identify that academic research has a hard time keeping up with the fast-paced technological environment which is why recruitment industry tries to push the limitations of reasonable hiring practices.

Further, Bankins et al. (2022) probe into the topic of AI decision-making and its impact on workers' insights of fairness in an HRM context. The findings stress the significance of managers being experienced in the capacities of AI and identifying the dangers connected with seeing AI as a cause of extra amount of work. This assessment is

critical as the perception of AI as a "techno-stressor" can considerably induce how workers distinguish the objectivity of AI decisions and consequently influence their behavioural responses. By highlighting the necessity for training for managers on the functionalities of AI and the probable stressors it may introduce, Bankins et al. (2022) emphasize the impact of concentrating on these problems proactively. This practical tactic can help mitigate negative perceptions of AI decision-making processes and foster a more positive managerial environment where AI is examined as an instrument that improves rather than lessens from the justice and well-being of workers. In conclusion, the study by Bankins et al. (2022) casts a light on the key role of managerial understanding and training in shaping workers' insights of AI decision-making in HRM. By recognizing and addressing the risks presented by AI, organizations can encourage a culture where AI is combined sensibly and ethically, aiding to a more appropriate and helpful work environment.

2.6 Strategies for mitigating bias and ensuring fairness

Discrimination and biased practices in the recruitment industry are an imminent issue and require immediate attention and understanding since recruitment has a deep impact on the livelihoods of people, as well as workplace practices. The “automated hiring systems” (AHSs) are rapidly replacing conventional methods of selection of candidates, raising questions about whether AHSs are practically ethical, whether they present biases fed in the system by programmers and its creators, and whether we are delineating human emotion and sincerity from the selection process. According to Myers (2023), 97.4% of Fortune 500 companies use Applicant Tracking Systems (ATS), among which, over 38% use Workday for talent acquisition. Applicant Tracking systems are designed to “process automation, interview scheduling, resume parsing, and documentation delivery. Some can even perform native ATS background checks as necessary” (Johnivan, 2024). Scholars are suggesting that “technology is disrupting the talent identification industry” especially

because there is a lack of credible, scientific research on these innovative assessment tools (Chamorro-Premuzic et al., 2016).

One of the challenges for mitigating ethical issues that come with automated recruitment systems is that most of the ATSs and AHSs are produced in the United States of America, which means that they don't take in to account the legal aspects in other parts of the world, hence, the body of research work on bias is currently concentrated around the US work environment (Sanchez et al., 2020; Pena et al., 2020). There is also a lack of qualitative data surrounding AHSs (Sanchez et al., 2020).

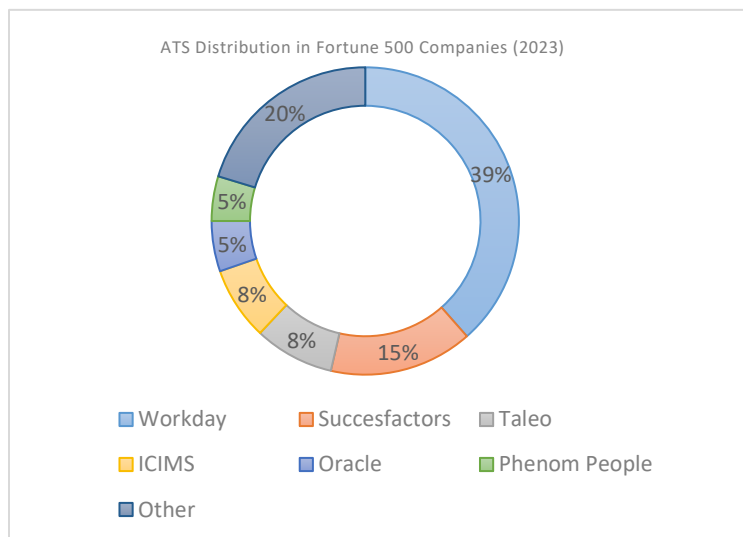


Figure 4: ATS Distribution in Fortune 500 companies in 2003 (Myers, 2023).

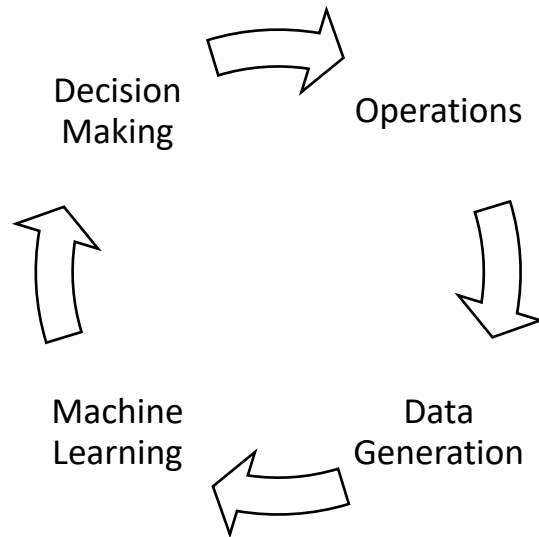


Figure 5: Life Cycle of AI-Supported HR Practice (Tambe et al., 2019)

Tambe et al. (2019) outline HR challenges that present themselves when it comes to application of AI techniques. Firstly, understanding a “good employee” is a complex idea because it is multifaceted especially that an employee’s performance is merged with group performance, hence, making performance evaluations redundant. Secondly, Tambe et al. (2019), talk about the rarity of some events occurring in smaller companies whereas data science requires large number of observations (also see Cappelli, 2017). Lastly, the challenge lies in picking the right person based on fair practices as HR decisions have dire consequences for many. Tambe et al. (2019) question the “explainability” aspect of hiring, “knowing what attributes are driving the decision”- meaning that employment requires many socio-psychological concerns which cannot be catered by automated systems. Keeping these challenges in view, Tambe et al. (2019) depict a traditional AI life cycle (see Figure 6 and Table 3).

Table 5
AI Life Cycle Phases and functions (Tambe et al. 2019)

AI Life Cycle phases	Functions
Operations	How organizations hire employees, these include administrative tasks
Data Generation	Information systems, ATS are all inputs for this stage.
Machine Learning	“a broad set of techniques that learn from data to create algorithms, typically to predict outcomes” (Tambe et al. 2019)
Decision Making	The way in which employers utilize insights from machine learning phase in daily operations, in the case of recruitment, how much they depend on this information to select a candidate.

Challenge	Response			
	Data generation	Machine learning	Decision making	Operations
Complexity of HR outcomes	Solicit employee contributions into outcomes' metrics and create consensus around them	Train algorithms for a few outcomes	Managers' discretion on the basis of the algorithm's predictions Run experiments whereby an algorithmic or human decision is randomly assigned to individual cases	Monitor the medium- and long-term validity of AI-based decisions Periodically review and retrain the algorithm
Small data	Integrate HR data with financial and operational data Use fine-grained real-time data Use vendors' data collected from larger populations	Use vendor-trained models Use causal models	Let managers act on algorithm's recommendations according to prespecified guidelines	
Accountability regarding fairness, ethical norms, and labor laws	Assess the consistency of human-made decisions used for training the algorithm	Create consensus around fairness criteria Weigh multiple fairness criteria Use causal model Ask data scientists to explain the model (identify the features that disproportionately affect its predictions)	Make random choices with probabilities predicted by the algorithm	Specify a code of ethics for AI-related initiatives Create an AI Council with representatives of all stakeholders
Employee reactions	Collect data to improve processes first	Create employee consensus around the features used to train the algorithm	Maintain managers' responsibility for AI-based decisions Create an appeal process	Regularly solicit employee feedback Monitor employee engagement

Figure 6: Figure taken from Tambe et al.'s (2019) study on possible responses to

challenges of AI.

The complexity of judging what makes a “good employee” presents itself as a challenge because it is not easy to measure individual performance as biases may be present, job requirements may be broad, and they may also simply because the employee may be working in a group setting (Murphy, 1991). Tambe et al., (2019) offer a few ways to mitigate this issue in HR settings- by including “financial performance data at the organizational level closest to employee control, seeing how individual performance affects larger business units and the company as a whole”, and utilizing some subjective matters such as employee’s coherence with company culture along with objective measures. For other ways of mitigating challenges from varying stages of the AI life cycle outlined in the study of Tambe et al. (2019), please refer to Figure 6.

As companies are in the era 3.0 of Digital Recruiting as compared to the Analog Recruiting era of 1990’s, companies can now effectively advertise, attract, assess, interview and screen best candidates for their companies. Black and van Esch (2020) present some suggestions to the managers in their insightful study that dives deep into the history of recruitment and benefits of shifting to using AI in HR practices. They begin by suggesting that managers should initiate by applying AI-enabled tools to limited groups of candidates because over approximately 80% of large organizational change proposals tend to fail (Black & Gregersen, 2013). Secondly, they suggest deliberately neutralizing biases in the AI system and “not allow it to freely learn”. Thirdly, they suggest building an integrated system where the candidate is viewed as a “customer”. Although many would still object to this claim, however, van Esch et al. (2019) suggest that AI tools are more objective and less biased than humans which is the reason why candidates prefer engaging with an AI tool over humans because they see them as convenient and novel. This candidate perception makes a company come across as “cutting-edge” (Miles & McCamey, 2018),

hence, being transparent about the use of AI tools in the recruitment process is a necessary step HR managers should take. Lastly, Black and van Esch suggest that the final interview should not be with an AI chatbot but instead be with a human as at the end of the day, the selected employee must work in a company that has human employees and not AI chatbots as team members. Similarly, to mitigate discrimination and bias from AI models in recruitment, Pena et al. (2020) present a groundbreaking experimental framework called “FairCVtest” , which is made publicly available, to study how “multimodal machine learning is affected by biases present in the training data”. The study concludes that the most common approach to studying algorithmic discrimination is through group-based bias (Serna et al., 2019), however, in the future, they want to update FairCVtest to use user-specific bias approach in addition to group-based bias approach. Pena et al. (2020) describe it as:

“The framework is designed as a fictitious automated recruitment system, which takes a feature vector with data obtained from a resume as input to predict a score within the interval $[0, 1]$ Each resume is scored using a linear combination of the candidates competencies and the suitability attribute, adding a slight Gaussian noise to introduce a small degree of variability. Since we're not taking into account gender or ethnicity information during the score generation, these become agnostic to this information and should be equally distributed among different demographic groups.”

Pena et al. (2020) also use SensitiveNets to improve just practices in the AI recruitment models and suggest that companies should focus on removing susceptible data during the learning process instead of removing at the input stage. Similarly, another imminent issue in recruitment and utility of AI is discrimination against disabilities. Reviews of equality in Recruitment AI for people with disabilities have consequently acknowledged little consideration or have been ignored. The US Federal Government has

gone even further to state that the hiring tools could be violating civil right laws (The Associated Press, 2022) A white paper produced by Nugent et al. (2020; Nugent & Scott-Parker, 2022) factors the effects to and fears of disabled job applicants employing AI systems for recruitment and presents suggestions on the steps employers can take to safeguard improvement in recruitment which is just to all candidates regardless of their challenges. In doing so, the white paper extends the argument that making systems reasonable for disabled job applicants guarantees that AI recruitment systems are adequate for everyone. Nugent et al. (2020) pose critical questions that companies need to ask when employing AI technology for recruitment and selection processes. These include but are not limited to: Does the technology align with company values of diversity and inclusion? Does the technology align with the company's principles of ethical and responsible usage of Artificial Intelligence? What are the pros and cons for disabled candidates when using AI technology? Would HR require alternative evaluation methods for candidates with impairments? Similarly, Tilmes (2022) outlines a "disability justice approach" which is a framework for centering disabled people's experiences in the algorithm. Rigotti and Fosch-Villaronga (2024) suggest that because of the multi-disciplinary and multifaceted nature of the subject of AI and its ethical challenges, we cannot pick and choose a single discipline to resolve this complex issue. Instead, the future of AI research lies in a cross-sectoral and cross-disciplinary collaborative approach. For example, the BIAS project and FINDHR are EU-based projects that develop innovative technologies to detect bias through capacity building, and integrating human expertise in AI hiring, respectively. Further, Rigotti and Fosch-Villaronga (2024) recommend using a diverse team with varying sexual orientations, genders, race, ethnicities, ages, and people who are differently abled so such human experiences can be integrated into the automation processes and algorithms.

In terms of addressing gender bias in recruitment and selection processes using AI technology, as established previously using the case of Amazon, it is significant to initially outline contributing factors to investigate how these biases make their way into the algorithmic systems. As discussed earlier through the works of Peng et al. (2019), the catalyst could be the overall world distribution system or preferences of certain jobs. Additionally, it is also the lack of female employees globally in the tech industry, and especially in Artificial Intelligence and data science research (Nadeem et al., 2020). Scholars call for new frameworks which are gender-focused and mitigate past unfair practices (Trewin, 2018; Gummadi & Heidari, 2019; Dwivedi et al., 2021). Further, Drage and Mackereth (2022) analyse two important prerogatives presented by recruitment AI companies in relation to the expansion and distribution of AI-powered HR tools: (1) recruitment AI can accurately evaluate candidates by eliminating gender and race from their systems, and (2) this exclusion of gender and race will make recruitment better, help customers attain their “Diversity, Equity, and Inclusion” (DEI) objectives, and establish the fundamentals for a justly merit-based ethos to flourish within a company. The authors contend that these statements are deluding for four reasons: First, efforts to “strip” gender and race from AI systems often misapprehend what gender and race are, casting them as separable characteristics rather than broader systems of power. Second, the attempted subcontracting of “diversity work” to AI-powered hiring tools may inadvertently embed cultures of discrimination and bias by failing to tackle the systemic problems within companies. Third, AI hiring tools’ theoretically unbiased evaluation of candidates’ attributes oppose the power relationship between the spectator and the one being examined. Precisely, the racialized history of character analysis and its related methods of sorting and labelling play into longer histories of systematic categorisation and imitate the present demands and requirements of the job market, even when not openly directed along the lines

of gender and race. Lastly, AI tools for recruitment assist in creating the “ideal candidate” that they allegedly recognize through by forming connections between text and physical, live humans. For the purpose of tackling these issues Drage and Mackereth (2022) offer some recommendations in their insightful body of work: 1) Stakeholders who are responsible for creating these AI tools for recruitment need to look beyond isolated instances of bias and focus on broader instances of inequalities that shape the recruitment and selection processes (Also see Kalluri, 2020). 2) HR professionals should not let the excitement of integrating new technologies and big data into HR practices cast a shadow over learning more about the limitations of AI. 3) HR and companies should demand more knowledge from AI regulators, policymakers and ethicists about the legislation and deep scrutiny of the utility of AI in recruitment. And 4) Future research must question how the so-called neutral AI technology does in fact create bias in the hiring process.

Additionally, Ferrara (2023), through a methodical review of present and past literature across various academic fields, exhibits definitions of AI prejudice and its different styles, containing a thorough inspection of “generative AI bias”. The author examines the destructive effects of AI bias on people and society and supplies an outline of existing attitudes to lessen AI bias, involving “data pre-processing, model selection, and post-processing”. The author highlights the exceptional risks rendered by generative AI models and the value of approaches explicitly moulded to tackle these. Focusing on prejudice in AI necessitates a complete approach involving varied and demonstrative datasets, improved transparency and responsibility in AI systems, and the examination of alternate AI models that prioritize equality and ethical deliberations. This study supports the ongoing dialogue on fostering fair and unbiased AI systems by granting a synopsis of the resources, effects, and modification approaches related to AI bias, with a individual focus on the developing domain of generative AI. However, it is important to outline that

like every field, the study of AI bias is riddled with limitations. Since we previously mention group fairness approaches, it is important to highlight that focusing too much on group bias may lead to unfair treatment of individual experiences. Whereas, focusing on individual experiences may lead to neglecting group's shared experiences. Another challenge in mitigating AI bias is defining the idea of "fairness" as these definitions are contextual (Also see Fu et al. 2020). Additionally, there is a lack of qualitative assessment of human behaviour and recruitment experiences with AI tools. We have a lot of literature which present quantitative datasets but overlook the complexity of human nature. Figure 7 has Ferrara's (2013) summary of these limitations.

Approach	Description	Examples	Limitations and Challenges
Group Fairness	Ensures that AI systems are fair to different groups of people, such as people of different genders, races, or ethnicities. Aims to prevent the AI system from systematically discriminating against any group. Can be achieved through techniques such as re-sampling, pre-processing, or post-processing the data.	1. Re-sampling techniques to create a balanced dataset. 2. Pre-processing or post-processing to adjust AI model output.	1. May result in unequal treatment of individuals within a group. 2. May not address systemic biases that affect individual characteristics. 3. Group fairness metrics may not consider intersectionality.
Individual Fairness	Ensures that AI systems are fair to individuals, regardless of their group membership. Aims to prevent the AI system from making decisions that are systematically biased against certain individuals. Can be achieved through techniques such as counterfactual fairness or causal fairness.	1. Counterfactual fairness ensuring the same decision regardless of race or gender.	1. May not address systemic biases that affect entire groups. 2. Difficulty determining which types of fairness are appropriate for a given context and how to balance them.
Transparency	Involves making the AI system's decision-making process visible to users.	Making AI system's decisions and processes understandable to users.	Different definitions of fairness among people and groups and changing definitions over time.
Accountability	Involves holding the system's developers responsible for any harm caused by the system.	Developers held responsible for unfair decisions made by AI systems.	Determining responsibility and addressing potential harm.
Explainability	Involves making the AI system's decisions understandable to users.	Providing clear explanations of AI system's decisions.	Addressing the complexity of human behavior and decision-making.
Intersectionality (not explicitly mentioned as an approach, but it is an aspect to consider)	Considers the ways in which different dimensions of identity (such as race, gender, and socioeconomic status) interact and affect outcomes.	Developing AI systems that consider the interaction of different dimensions of identity.	Addressing the complexity of intersectionality and ensuring fairness across multiple dimensions of identity.

Figure 7: Summary of limitations in literature on AI based hiring processes presented by Ferrara (2013).

It is well-established that AI has much to offer in the recruitment process specifically when it comes to expediting the recruitment process, however, it is also well-established that AI recruitment systems are riddled with inevitable biases. This is driven

from the idea that AI systems replicate what is encoded in them i.e. human biases are eventually translated into algorithms. Soleimani et al. (2021) survey 35 HR managers and come to the conclusion that to resolve these biases, it is important for HR teams to collaborate with AI developers- knowledge sharing can improve machine learning models by informing “data labelling”. Supporting this idea, Raghavan et al. (2020) present an insightful analysis of pre-employment assessments where they determine that vendors of AI recruitment process tools are not transparent and not “forthcoming about their practices”, along with disparate impact vendors should also focus on “differential validity”, and lastly, that there is a dire need to revisit legal standards of machine learning. Similarly, Fu et al. (2020) examine the definition, and the perceptions of fairness policy makers, experts, and academic researchers have worked on and offered. They conclude that the nature of “fairness” is complex, contextual and in some scenarios, incompatible to each other (“cannot be satisfied simultaneously”). Further they comment on the challenges in distinguishing and revealing algorithmic bias given the perceived decision outcome. Finally, the paper discusses how agents’ strategic behaviour may lead to biased societal outcomes, even when the algorithm itself is unbiased. The paper instead suggests having a deeper look in to comprehending why human biases arise and how human bias is reflected in data and algorithms.

The application of Artificial Intelligence in Human Resource Management is considered one of the most innovative trends in the recruitment and selection processes (Upadhyay & Khandelwal, 2018). In the recruitment of new employees, AI can make resume scanning and extraction of job relevant information from thousands of candidates’ profiles easier and convenient (Kaczmarek et al. 2005). Despite its booming popularity among companies and HR, AI powered recruitment is concerning for many reasons especially when it comes to dehumanizing, biases, and discrimination against certain

groups such as women, disable, people of colour, people of varying genders etc. Another challenge is that of privacy- vendors of AI based recruitment tools are not transparent about how the algorithms operate and what they do with the data that is fed in to them when candidates are applying through them. Although AI-based recruitment cannot be separated from companies, it is important to tackle these challenges as they pose a threat to livelihoods.

CHAPTER III: METHODOLOGY

3.1 Research Philosophy

Research philosophy is concerned with the nature and knowledge of the study. Essentially, there are five main research philosophies pragmatism, positivism, critical realism, interpretivism and postmodernism (Saunders et al., 2019). These principles are necessary to inform how data for research should be gathered, investigated and utilized. Pragmatism, a philosophy most common in the United States of America, argues that the “truth of an idea is found in its consequences” (Gillespie et al., 2024, pg.1). Pragmatism holds the proposition that researchers should work with the research methods according to the research problem at hand which makes it often associated with mixed-methods approach (Kaushik & Walsh, 2019). The scholars that supported pragmatism argued that reality cannot be inquired by social sciences only using one empirical approach (Maxcy, 2003). Positivism, on the contrary, supports the idea that knowledge can be confirmed by observing and objective measurement. This philosophy most commonly finds its origins in natural sciences and mostly used in quantitative data analysis (Park et al., 2020). Further, critical realism is a branch of philosophy that differentiates between the “real” and the “observable” world, where “the real can not be observed and exists independent from human perceptions, theories and constructions” while “unobservable structures cause

observable events and the social world can be understood only if people understand the structure that generate events” (Warwick, n.d.). Critical Realists assume “the existence of an objective world that has powers and properties that can be more accurately known as a consequence of scientific endeavour but recognize that knowledge is a subjective, discursively bound and constantly changing social construction” (Vincent & O’Mahoney, 2016). Interpretivism in research philosophy is essentially a qualitative approach with a focus on individual’s belief system and reasoning- it essentially views reality as socially constructed meaning that reality is constructed through culture, language, shared beliefs and meanings, and consciousness (Nickerson, 2024). Lastly, postmodernism rejects the idea of a static, universal foundation of reality. The argument is that reality is dependant on culture, culture changes with time, context and with community. Briefly, reality is not the same for everyone. Postmodernism is most common in the disciplines of art and social sciences where social scientists challenge conventional methods of looking at reality and instead, offer a deconstructed version of it which is based on varying spatial and temporal aspects.

For the purpose of this study, the closest research philosophy to this research study is interpretivism. This dissertation aims to understand the experiences of different sets of people, and in varying contexts such as from the perspective of job applicants and from the perspective of HR managers. This dissertation also takes into account the contextual basis of the study. At the core of interpretivist approach is the understanding that experiences vary from one person to another, it is significant that interpretivists understand these contexts so they can make informed interpretations of the data (Thahn & Thahn, 2015). Interpretivism is also called “anti-positivism” because of its non-conformity with the model of natural sciences because human experiences cannot be objectively “known”- such as emotions, values, ethics, biases, history- the search is not for an objective truth but to create

understanding. In most research studies where this concept of understanding subjective reality is present, qualitative methods are inherited. The focus of this dissertation is also exploring human experiences around AI-based recruitment and selection processes. Hence, interpretivism is the best fit. However, interpretivism presents certain limitations, such as the “validity” of qualitative research is questionable as the experiences shared by people surveyed maybe misconstrued, lied about, exaggerated, or simply made up. Another limitation is that interpretivism can be excessively subjective making objectivity entirely absent from the proposed study. And lastly, the interpretation by researchers can vary and may present biases.

Metatheoretical Assumptions About	Positivism	Interpretivism
Ontology	Person (researcher) and reality are separate.	Person (researcher) and reality are inseparable (life-world).
Epistemology	Objective reality exists beyond the human mind.	Knowledge of the world is intentionally constituted through a person's lived experience.
Research Object	Research object has inherent qualities that exist independently of the researcher.	Research object is interpreted in light of meaning structure of person's (researcher's) lived experience.
Method	Statistics, content analysis.	Hermeneutics, phenomenology, etc.
Theory of Truth	Correspondence theory of truth: one-to-one mapping between research statements and reality.	Truth as intentional fulfillment: interpretations of research object match lived experience of object.
Validity	Certainty: data truly measures reality.	Defensible knowledge claims.
Reliability	Replicability: research results can be reproduced.	Interpretive awareness: researchers recognize and address implications of their subjectivity.

Source: Class notes provided by Jörgen Sandberg.

Figure 8: Comparative Analysis of Positivism and Interpretivism from Medium's article by Soleymani (2017).

3.2 Research Strategy

Two main research strategies studies can adopt are quantitative and qualitative research. Qualitative research has constructivist, and by extension, interpretivist paradigms which seek to thoroughly comprehend the subject rather than prediction of outcomes (Tomaszewski et al., 2020). Like Interpretivism, qualitative research strategy seeks to understand, appreciate, and comprehend people's lived experiences, believes in subjectivity, and helps to respond to inquiries about people and their lives (Lincoln & Guba, 1985). On the other hand, quantitative analysis implies yielding outcomes from numbers and statistical data. The aim of the dissertation is to gain data that encompasses the experiences of people who have gone through recruitment and selection processes involving AI-based tools like chatbots to figure out whether they have faced any form of discrimination or felt that their experience has made them feel discriminated against by the algorithm. The dissertation also seeks to get the HR managers' point of view on integrating AI-based recruitment tools in their companies, their experiences in getting best candidates, effectiveness of AI, whether they feel like their jobs are being taken away, and ethical considerations surrounding AI. It is important to highlight that qualitative research has contested definitions but the most concise one can be found in the works of Denzin and Lincoln (2011, pg. 2):

“Qualitative research is multimethod in focus, involving an interpretative, naturalistic approach to its subject matter. This means that qualitative researchers study things in their natural settings, attempting to make sense of, or interpret, phenomena in terms of the meanings people bring to them. Qualitative research involves the studied use and collection of a variety of empirical materials – case study, personal experience,

introspective, life story, interview, observational, historical, interactional, and visual texts – that describe routine and problematic moments and meanings in individuals’ lives.”

Because of its multi-method characteristic, Qualitative analysis has the advantage of being flexible in nature which ultimately allows the researchers to have a thorough understanding of the subject matter. Therefore, this dissertation seeks a qualitative approach as the best fit method for research. Qualitative research will grant this dissertation to be able to gather information through limited amounts of interviews regarding about how AI is applied in recruitment and selection processes in various companies. Qualitative research approach is useful as the topic of this dissertation calls for collection of personal information conducted from specific organizations which also includes understanding people’s sentiments surrounding the sensitive topics of bias and discrimination, information which is based on being qualitative and could not be obtained through numbers or statistics. However, to determine and solidify factual basis deduced from survey and interview responses, this research also utilizes the online statistical tool JASP analytics to identify mean, median and mode of the data, and to draw scatter plots to show upward and downward trends.

3.3 Research Approach

This dissertation adopts an inductive research approach. Inductive research, also called “bottom-up” approach, is exploratory, takes observations and looks for patterns in the data (Woo et al., 2017). Further Thomas (2006) outlines three general purposes for using an inductive approach: a) to compress raw data into a compact format, b) to establish relations between research objectives and the findings from raw data, and c) to develop a framework. The study aims to explore the effects of technological advancements on HR practices, their effectiveness in the recruitment business and looking for interrelated patterns in past literature.

3.4 Literature Review

The researcher has chosen a thematic literary review of past and present literature on the topics of Artificial Intelligence, Human Resource Management, bias in recruitment, and strategies to mitigate these biases. The aim of utilizing a thematic approach for the literary review is that it enables a transparent and plain overview of what the previous research have covered in relation to the issue which this dissertation intends to investigate. As a thematic literary review has a focus on comprising a specific area and the topics developing from that, it seemed the most fitting for this dissertation in order to explore recruitment and technology within HR recruitment practices (Broadhurst & Harrington, 2016). The themes were identified by exploring main ideas researched in previous journals and from there sorting it into themes which would best acquire and depict what had been earlier researched. For the purpose of this dissertation, the researcher concluded four main themes

- AI's impact on efficiency and challenges
- Ethical considerations and fairness
- Bias and discrimination in AI recruitment
- Strategies for mitigating bias and ensuring fairness

For each theme, 10 scholarly articles were initially gathered. See Table 5

Table 6
Secondary sources divided by themes.

Theme	Journal	Conference	Book/Book	Websites
	Articles	Papers	Chapters	
AI's impact on efficiency and challenges	7	2		1

Ethical considerations and fairness	7	3	
Bias and discrimination in AI recruitment	7	2	1
Strategies for mitigating bias and ensuring fairness	6	4	

The key words were used when searching for literature were “Artificial Intelligence” or AI, “Human resource management” or HRM, “Recruitment and selection process” “AI in recruitment” , “Bias and discrimination through AI”. A wide selection of journals covering the themes were found through a comprehensive pursuit on existing literature. The secondary data gathered from various papers will guide this dissertation to label what themes and sub-themes have already been covered by previous literature and where in the research there is a gap that could be filled or multiplied through this dissertation. Key journal sources included Taylor Francis, Sage Pub, PubMed, Science Direct, Elseviers, JStor, and Google Scholar.

3.5 Data Collection

3.5.1. Data Collection Method

The data collection methods used include both primary and secondary data collection. For secondary data collection, this dissertation has utilized book chapters, conference paper, journal articles and credible blogposts and websites. For primary data collection, the researcher has divided the intended samples to be divided into three main categories: HR professionals, job applicants or candidates, and experts on Artificial Intelligence. Observations, focus groups, surveys, and interviews are some of the most popular data collection methods for qualitative analysis (Gill et al., 2008). We previously explored the nature and objectives of qualitative analysis, the data collection method for qualitative analysis purposes also includes interviews. A part of our data collection includes semi-structured interviews with AI experts. Fundamentally, there are three types of interviews- structured, semi-structured, and unstructured interviews. Structured interviews are pre-planned and have predetermined questions, while semi-structured interviews allow room for follow-up questions. They have several key questions that directly resonate with research themes and focus areas, but also allow the person being interviewed to explain an idea in detail. On the contrary, unstructured interviews don't have a game plan and progress based on initial questions asked (Gill et al. 2008).

3.5.2. Data Collection Process

For the purpose of choosing the sample size, I have chosen the following equation:

$$N/1+Ne^2 \quad N=\text{total population} \quad e=\text{error}$$

Job applicants (German speaking market)/ Professionals with academic background

$$24,600,000 / 1 + (24,600,000) \times (0,05)^2 \quad \text{Confidence Level } .95\% = 400$$

HR Professionals (Recruiter) (German speaking market)

$$50,000 / 1 + (50,000) \times (0,05)^2 = 396$$

AI HR Experts (German speaking market)

5700

$$5,700/1+(5,700) \times (0,05)^2 = 373$$

Table 7
Information of the Interviews

Interviewee	Title	Experience in HR or recruitment	Date of the interview	Duration	Gender	Location of the company
Sebastian B.	Freelance AI Expert	Banking and Financial Services			Male	Freelancer
Yvonne B.	HR Business Partner	Financial Services Company				
Christoph K.	Job Seeker				Male	
Nashara T.	AI Expert/ Project Manager	Recruitment Consultancy			Female	
Casandra S.	Head of Recruitment	Investment Bank			Female	

Daniel S.	Job Seeker/	Digital	Male
	Manager	Corporate	
		Bank	
Dogan Ki	Project	Management	Male
	Manager	Consultancy	
Federica A.	HR Manager	Financial	Female
		Service	
		provider	

3.6 Method for Data Analysis

Thematic analysis was chosen to analyse data. This method was chosen based on the initial research paradigm of interpretivism, as thematic analysis is a suitable method for this paradigm (Peterson, 2017). Thematic analysis is used to identify patterns in a data set leading to new perceptions or knowledge (Elliot, 2018). Thematic approach is based on reducing down the qualitative data, for an example by coding the conducted interviews, and picking out emerging and repetitive themes. A thematic analysis is very adaptable in its character and is therefore appropriate for many research areas (Maguire & Delahunt, 2017). The themes identified through the thematic analysis will be acting as the main points of data analysis and contrasted to the theoretical framework as well as the chosen model.

3.6.1. Themes and Coding

Braun and Clarke (2006) describe a theme as:

“A theme captures something important about the data in relation to the research question and represents some level of patterned response or meaning within the data set. An important question to address in terms of coding is: what counts as a pattern/theme, or what ‘size’ does a theme need to be? This is a question of prevalence, in terms both of space within each data item and of prevalence across the entire data set”.

Naeem et al. (2024) outline and summarize Braun and Clarke's (2006) six steps of thematic analysis (See Table 3) which this dissertation utilizes to generate its own themes.

Table 8

Braun and Clarke's (2006) six steps for thematic analysis.

Steps	Description
Familiarization with Data	Noting down primary ideas through transcription
Producing Initial Codes	Coding features of data that stand out and repeat, then collating data to each code
Looking for Themes	Organising codes in to potential themes.
Examining Themes	Checking if themes work in relation to codes from step 1 and step 2. Make a "Thematic Map".
Define and Name Themes	Generate names for each theme
Produce Report	Final opportunity for analysis

According to Braun and Clarke (2006), firstly, data is collected from the interviews which is then transcribed into a written document, listened to and read various times. In the second phase, initial codes are generated from the transcribed data. In the case of this dissertation, the pre-established codes were conventional recruitment practices, artificial intelligence or AI, effectiveness, time management, technological advancements, automation, talent acquisition and human resources or HRM. Additional codes which emerged during the analysis of the data were bias, discrimination, ethical risks, human behaviour, prejudices, privacy, screening and talents. In the third phase, the recognized codes were carefully analysed and contemplated upon how to bring together in order to create a theme. In the fourth step, that is reviewing themes, researcher elaborated on the

identified themes. In the fifth phase, concise definitions and names were generated for each identified theme that will be presented in analysis part of the dissertation. Finally, the sixth phase of the model allowed researcher to perform the final analysis and put together the dissertation with finalized themes (Braun & Clarke, 2006). In Table 4, an overview of the finalized themes is presented

Table 9
Summary of themes used in the dissertation.

Theme	Description
AI's impact on efficiency and challenges	This theme describes the growing popularity of the usage of AI in selection processes especially after the COVID pandemic which necessitated work from home and more online interviews than in-person. Along with the efficiency that AI tools have provided to companies in their hiring processes, this theme also talks about challenges.
Ethical considerations and fairness	This theme provides an insight on ethical risks that AI poses and explores varying definitions of fairness.
Bias and discrimination in AI recruitment	This theme dives deep into instances of racial and gender bias in AI-powered recruitment processes. It talks about human's inherent nature of being prejudiced and how it reflects in coding algorithms for machine learning.

Strategies for mitigating bias and ensuring fairness	This theme explores strategies for minimizing bias and ethical risks through research and practical recommendations for future work.
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3.7 Research validity and reliability

Within qualitative analysis, it is notable to have the ability to express the validity and reliability of the accomplished research. The idea of validity can also be counted as the credibility of the research and it relates to the degree to which the claims, explanations and findings that are yielded through research express the study they are presumed to relate to. Numerous considerations such as inadequate samples, flawed methods and misleading measurement can weaken validity in research (Collis & Hussey, 2014). Reliability is defined as the repetition of findings and the consistency of the data. Repeatability means that if another researcher were to research the same study again it should yield the same results (Collis & Hussey, 2014). Every research is prone to be riddled with researcher's own beliefs, views, expectations and interpretation which can have an effect on the reliability of the research. During the data collection for this dissertation, it was noted that with the ample number of interviews, the same themes were in repetition.

CHAPTER IV:

RESULTS

4.1 Introduction

The entry of Artificial Intelligence (AI) into scenarios of recruitment processes, as well as capturing, evaluation and selection of candidates in modern companies, is a more than powerful currency in the game today. Finally, in this chapter, we present our quantitative and qualitative data analysis results in order to address the research questions with a full understanding of AI based recruiting systems. Combining the results from an integrated survey and interview we apply the insights to the problem of the intersection of technological efficiency and ethical human centric practices in recruitment.

The context for this chapter is the growing popularity of AI tools like Applicant Tracking Systems (ATS), Machine Learning, and bots to screen/match candidates and to schedule their interviews. The advantage of these is that these are quicker decisions and did not require administrative work. But they don't bring any, mind, because they can also raise some very important questions, about bias, transparency, dehumanization and the ethical implications of automated decision making in recruitment, among others. An analysis of these dualities in accordance with the complexity of using AI in human resource practices are made in this chapter (Bujold et al., 2023).

This chapter returns to the main purposes of the study in order to ground research objectives in the findings. By using the research, we work out how AI could improve recruitment efficiency going through fairness and ethical challenges (Hunkenschroer and Luetge, 2022). The study particularly looks specifically at how AI affects the candidate experience in recruitment; recruitment outcomes; and organisational strategies. Additionally, it examines the perspectives of HR professionals and AI professionals who

offered their thoughts about how recruitment is utilizing AI driven tools and what is be done to prevent biases and dehumanization (Fritts and Cabrera, 2021). This chapter addresses these objectives by identifying recruiter's implementation in adapting to the new reality with regards to AI.

Such goals are drawn out through a mixed methods approach based on statistical and thematic analysis. Using quantitative survey data, descriptive statistics (mean, mode, median) were used to summarize trends and inferential techniques (regression and correlation analysis) were used to discover relationships between variables. By looking at these statistical tools it specifically yields the key patterns of adoption and impact of AI in recruitment based on what the HR professionals and AI experts think about that. This is complemented by analysis of qualitative data from interviews with participants which were thematically analysed to generate recurrent themes. Four key themes emerged: human vs. AI bias and fairness, the balance between humans and AI, and the balance between efficiency and automation and ethical and regulatory considerations. However, a comprehensive approach to this, which balances numerical trends with rich qualitative narratives, does allow for a robust exploration of the research questions. By combining qualitative depth with quantitative rigor, this chapter represents the first step in a more thorough exploration of the subtleties of how machine learning affects recruitment (Lim, 2024). These implications for wider discussions of how organisations can harness the potential of AI while keeping in mind ethical, fairness and human centred challenges of recruitment are discussed.

4.2 Qualitative Data Analysis

4.2.1 Descriptive Statistics

4.2.1.1 AI Expert Survey Result

- Mean

It was found that AI experts are only very moderately familiar with recruitment related AI technologies, such as machine learning, natural language processing (NLP), and predictive analytics. Across these technologies, the mean score for familiarity was 3.32 (on a 5-point Likert scale), indicating a general but not deep understanding of how these technologies may be used in recruitment processes. Its mode, which was 4 meaning that most of the respondents rated their familiarity as "Agree" indicates that there was a large proportion of respondents that were certain about knowing the core AI functionalities.

- Median

As expected, this metric had also a median score of 4, meaning that responses were skewed towards the higher end of the scale. Mean and median aligned for this shows that example set is on the homogeneous sample level consistency level with few outliers at either extreme of the scale. According to most respondents, practical examples of AI in recruitment include machine learning for screening and NLP for the resume parsing. It seems that these researchers are aware of these AI technologies in a manner that is largely robust and that will serve as an excellent foundation for further conversations about the good and the bad of using AI tools in recruitment.

- Efficiency and Future Evolution of AI in Recruitment

In the recruitment processes, AI experts had agreed that AI would help by making the process more efficient (Dwivedi et al., 2021). And for the most part, people agreed that AI removes enormous amounts of time spent on tasks like resume screening, interview scheduling, and candidate ranking – with a mean score of 4.19 a strong agreement. The mode at 5 suggested that the majority of respondents agreed strongly to AI's transformative efficiency. 4 was also its median, further reinforcing a consensus in the room about AI's potential to speed up recruitment. The areas of Applicant Tracking System (ATS) or

chatbot usage allow HR to reduce the tedious tasks and focus mainly on decision making. Many people contributed that predictive analytics, which predicts a candidate's success based upon historical data, was beginning to influence recruitment strategies.

Experts also looked to the future of AI, and were optimistic about how it will develop. Strong agreement (4.32 on a mean score) was demonstrated that AI would significantly alter recruitment in the next five years. Respondents would like more personalized and more accurate tools, like an AI system to determine emotional intelligence and cultural fit. While current technologies were still perceived as not being ready to address all these sophisticated aspects properly. This data underscores the dual promise and challenge of AI: There's no doubt to its efficiency, but it's going to have to evolve on deeper qualitative dimensions of recruitment to stay effective.

- Challenges like Bias and Fairness

A notable concern expressed by the survey was bias and fairness of AI driven recruitment systems. Agreement that bias presenting a significant challenge was mean score of 4.19, showing broad consensus that the issue is present. There was a wide-ranging mode that was 4, consistent with this mean, and substantial proportion of respondents considered fairness to be a pressing concern. Across participants, the median score was also 4, indicative of consistent perceptions.

And responders identified biases in AI usually arise from the data used to train algorithms. An example of this would be that a given dataset of historical recruitment data if biased can perpetuate discrimination against a certain demographic group. For gender and racial bias discussions, respondents pointed to AI tools that appeared to unintentionally favour the majority often because of the data on which they are based. The "black box" nature of the many AI systems also caused fairness concerns being linked to a lack of explanatory of decisions (Pedreschi et al., 2019). How to address these biases was

advocated for by respondents through regular audits and algorithm updates. These statistics portend the need for ethical prudence in the deployment of AI tools which make use of these statistics in order to prevent the perpetuation of unfair recruitment practices.

Ethical Considerations (Transparency, GDPR Compliance)

Ethical considerations became the most critical due to transparency and compliance with regulation such as GDPR (Minssen, Rajam and Bogers, 2020). Strong agreement on its importance was indicated by the mean score of 4.32 in the importance of transparency in AI decision making. The mode 5 suggested that most respondents considered the higher importance of clear communication when it comes to how AI systems make decisions. Experts also noted that GDPR data privacy compliance and data privacy concerns were also raised by them. Respondents said they want to know exactly how the candidate data is processed and stored by organizations. We suggested regular reporting of AI driven recruitment system algorithmic decisions on their fairness, as a way of building trust and accountability in such systems.

Table 10
AI Expert Survey Statistics

Survey Item	Mean	Median	Std. Deviation	N
Familiarity with AI Technologies	3.32	4	0.78	434
Efficiency of AI in Recruitment	4.19	4	0.65	434
Future Evolution of AI in Recruitment	4.32	4	0.62	434
Bias and Fairness as Challenges	4.19	4	0.7	434
Transparency in AI Decisions	4.32	4	0.68	434
Compliance with GDPR and Ethical Standards	3.95	4	0.74	434

4.2.1.2 HR Professionals Survey Results

- Familiarity and Usage of AI-Driven Recruitment Tools

Results of the survey showed that most HR professionals are not familiar and make little use of AI powered recruitment tools. Median score for familiarity with AI-based tools (e.g., Applicant Tracking Systems (ATS), candidate ranking algorithm, interview scheduling tools) was 2.62 (5-point Likert scale). Overall, the median score was 3 which means that although some were moderately familiar with these tools, many were not greatly experienced. In addition, these showed that the majority of respondents had low familiarity levels, as shown by a mode score of 2. However, the mean familiarity score for generative AI models (ChatGPT or GPT4) was 2.25 points lower at 2.25. Respondents mentioned often the lack of exposure or training on how to use these tools for recruitment tasks like interview simulations or tailor-made candidate interactions. As told in their use patterns, organizations mostly used simple AI tools such as ATS, while the more advanced AI applications were not used much.

It in turn implies that the HR industry was still early adopters of AI in recruitment processes. It's possible that organizations are not assigning adequate emphasis to AI training or resource allocation for more sophisticated recruitment tools because people are sometimes not familiar with AI. That's what underscores the need for more accessible AI training programs, as well as organizational support for integrating AI in HR practices.

- Perceived Impact on Efficiency and Human Interaction

The survey exposed differences of opinion about the effect AI would have on recruitment efficiency as well as human interaction. Respondents agreed moderately on the perceived efficiency of AI in streamlining recruitment process as mean score was 3.02. With respondent recognition that AI tools cut down administrative burden, such as resume screening, and interview scheduling, the mode score for level 3 indicated a balanced distribution of opinions.

But there were concerns around how AI will negatively impact how humans can interact with one another. Then we had the statement ‘AI driven tools have improved human interaction in the recruiting process positively which garnered the lowest mean score of 1.81 with the mode score being 2. This was a perception, in general, that the AI tools were detracting from the personal engagement between recruiters and candidates. However, respondents said automated systems often took over face to face interactions, rendering the candidate experience less personal (Nørskov et al., 2022). AI facilitates support of time and motion tasks and serves to improve operational efficiency, but it was charged without the ability to evaluate critical soft skills and cultural fit for which human interaction is necessary. These findings indicate a dual challenge: To truly leverage AI’s ability to be efficient, while still keeping human interaction at the centre of the recruitment. To retain valuable connections with candidates, organizations must create hybrid models incorporating AI’s operational benefits with human centred elements.

- Ethical Concerns and Compliance with Regulations

Recurring themes in the responses were ethical concerns, which had a mean score of 3.92 of concern regarding issues including bias, transparency and data privacy. A number of respondents mentioned that a lack of transparency in the mechanisms through which AI is decided was a big barrier to trust. 4, the median score, only confirmed these fears around the use of opaque algorithms for whom it is hard to understand how candidates are being scored and ranked.

As a critical concern, it emerged in compliance with regulations, such as the General Data Protection Regulation (GDPR). The mean score for O compliancy was 2.07, with mode 2 meaning that most organisations are not completely aligned with regulatory standards. Respondents universally discussed gaps in how candidate data is collected, stored and used, arguing that too often candidates aren’t being fully and clearly

communicated with prior to AI powered decisions being made. The findings lead us to realize that organizations should give high priority to ethical AI practices. Another approach to adopting AI is to make it transparent and compliant with mechanisms such as explainable AI (XAI) and regular audits to assure ethical and legal standards (Amir, Kumar and Nayyar, 2024). They are ways that can help increase trust between candidates and HR folks which leads to more fair recruitment practices.

- Dehumanization Risks

Among HR professionals, there was a great risk of dehumanization in AI driven recruitment. There was significant agreement measured by the mean score of agreement with the statement “AI makes candidates feel dehumanized or undervalued,” with a mode of 4 (agreement). When automated rejection emails and the lack of any personal touch meant that candidates felt they were nothing more than a data point as opposed to a human being, respondents also commented that (Lavanchy et al., 2023). There were many HR professionals who highlighted the reputational risks these perceptions could bring to an organization looking for top talent. They suggested hybrid models of recruitment that leverage AI efficiency alongside intentional, human-included relationships, so that candidates are respected at every point along the journey.

Table 11
HR Professional Survey Statistics.

Survey Item	Mean	Median	Std. Deviation	N
Familiarity with AI-Driven Tools	2.62	3	0.84	402
Perceived Efficiency of AI	3.02	3	0.72	402
Impact on Human Interaction	1.81	2	0.6	402
Ethical Concerns (Bias, Transparency)	3.92	4	0.71	402

Dehumanization Risks	3.96	4	0.69	402
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4.3 Inferential Statistics

4.3.1 Regression Analysis

Table 12

Regression Analysis: AI Efficiency and Human Interaction

Variable	B (Unstandardized Coefficients)	Std. Error	Beta (Standardized Coefficients)	t	Sig. (p- value)
AI Efficiency (Independent)	0.652	0.045	0.735	14.49	0
Constant	1.283	0.183		7.01	0

- Relationship Between AI Efficiency and Human Interaction

In the final section, to perform the regression analysis was to determine the impact of AI efficiency on the recruitment process and its human interface. To fully understand the regression table, the unstandardized coefficient (B) is 0.652, meaning for every unit increase in AI efficiency meaning that consumers regard AI as more efficient in providing their desired function they experience a 0.652 unit decrease in their perceived quality of human interaction. The implication of this is that there exists a trade off in measurable terms between recruitment operational efficiency and relational engagement. This inverse relationship is confirmed by the standardized coefficient (Beta) of 0.735.

A p-value (0.000) greater than 0.05 (the significance level) indicates that there is a very strong statistical relationship, and says that the relation is unlikely to have arisen by chance. The t-value of 14.49 also indicated the very strong predictor of AI efficiency

changing human interaction. This data highlights a critical challenge for organizations: With AI powered tools such as chatbots and Applicant Tracking Systems (ATS) becoming faster, more accurate at tasks like resume screening and scheduling, these tools take away opportunities for candidates to have additional, but perhaps more important, interaction with even recruiters (Nayak et al., 2024).

Qualitative insights gathered from HR professionals and AI experts also closely match these findings; the universal concern raised by them was the degree of depersonalization in recruitment, at the hands of AI. Most of the respondents felt that candidates feel disengaged or undervalued, interacting with automated systems (Olson et al., 2022). These concerns are quantitatively validated using regression analysis one that quantifies the negative impact on human interaction from AI efficiency.

So, to overcome this trade-off, organizations should adopt hybrid recruitment model. All these models are combining the power of AI with the empathetic and intuitive human recruiter aspects. For example, AI does not need to make critical decisions at stages of interviewing and holding feedback sessions, such as a recruiter should. Organizations can design recruitment processes that are optimized for AI efficiency and human collision, both creating a great experience for candidates and helping employers long-term.

Table 13
Regression Analysis: Bias Mitigation Tools and Fairness Perceptions

Variable	B	Std.	Beta	t	Sig. (p-value)
	(Unstandardized	Error	(Standardized		
	Coefficients)		Coefficients)		
Bias Mitigation Tools	0.481	0.038	0.698	12.66	0
(Independent)					
Constant	1.015	0.161		6.31	0

3.3.2. Impact of Bias Mitigation Tools on Fairness Perceptions

The second regression analysis explores the impact of implementing bias mitigation tools on the perceptions of fairness in AI driven recruitment. That is, the unstandardized coefficient ($B = 0.481$), which indicates that for every unit increase in implementation of bias mitigation tools, fairness perceptions will climb 0.481 units. Another way to highlight this substantial impact of these tools on fairness is with the standardized coefficient (Beta) of 0.698.

This relationship is confirmed to be statistically valid with the results of $t\text{-value} = 12.66$ and the $p = 0.000$ significance level. These results suggest that fair data tools, such as diverse and trained data sets and algorithmic audits, are central to combating fairness challenges. The tangible benefits of adopting fairness focused AI practices were perceived by respondents who reported using the tools; those using the tools reported fairness in their recruitment processes.

These findings are analysed with emphasis placed on practical implications. When an organization successfully integrates strong bias mitigation strategies into its AI system, it doesn't only improve fairness, it also makes for more trust among candidates and stakeholders. As the qualitative theme raises ethical considerations, the transparency and fairness in recruitment process are considered to be wide enough for the successful implementation of AI in recruitment (Balasubramaniam et al., 2023).

These regression results are actionable for HR professionals and AI practitioners. This zeroes in on bias mitigation tools and makes it possible to design a recruitment process or a pipeline for it to be efficient while also ensuring it is equitable; furthermore, such a process complies with ethical standards and resolves other risks inherent in the use of

biased AI systems. On this basis, it further advocates for the integration of explainable AI (XAI) to achieve transparency and candidate trust.

4.4 Correlation Analysis

Table 14
SPSS Correlation Analysis Table.

Variables	Pearson Correlation (r)	Sig. (p- value)	N
AI Familiarity and Ethical Concerns	0.674	0	434
Dehumanization Risks and Candidate Satisfaction	-0.598	0	402

4.4.1. Correlation Between AI Familiarity and Ethical Concerns

The results of the correlation analysis show a strong positive correlation between ethical concern and AI familiarity, with a Pearson correlation coefficient (r) equal to 0.674. Which is saying that the higher the familiarity people have with AI technologies, the more concern they have about their ethical implications bias, transparency, privacy of data. This is a strong positive association meaning if you have more or less familiarity with AI technologies, that you're also feeling more or less concern about these issues. Further, we validate the statistical significance of this relationship with a p-value = 0.000, meaning that the results are not random chance. The findings remained valid in the sense of sample size (N = 434). We find that those who are exposed to more AI technologies are more likely to recognise and understand the ethical aspects of how AI is used in recruitment.

Often, participants in these forums were people with advanced AI applications backgrounds such as natural language processing (NLP) and predictive analytics who

highlighted risks of bias in algorithms and opaque decision-making processes. The agreeable findings here with qualitative findings where AI experts highlighted the 'black box' nature of many systems as a key barrier to trust also. For example, respondents observed that AI models trained on historical hiring data tend to perpetuate existing biases, which disadvantage the underrepresented groups more disproportionately.

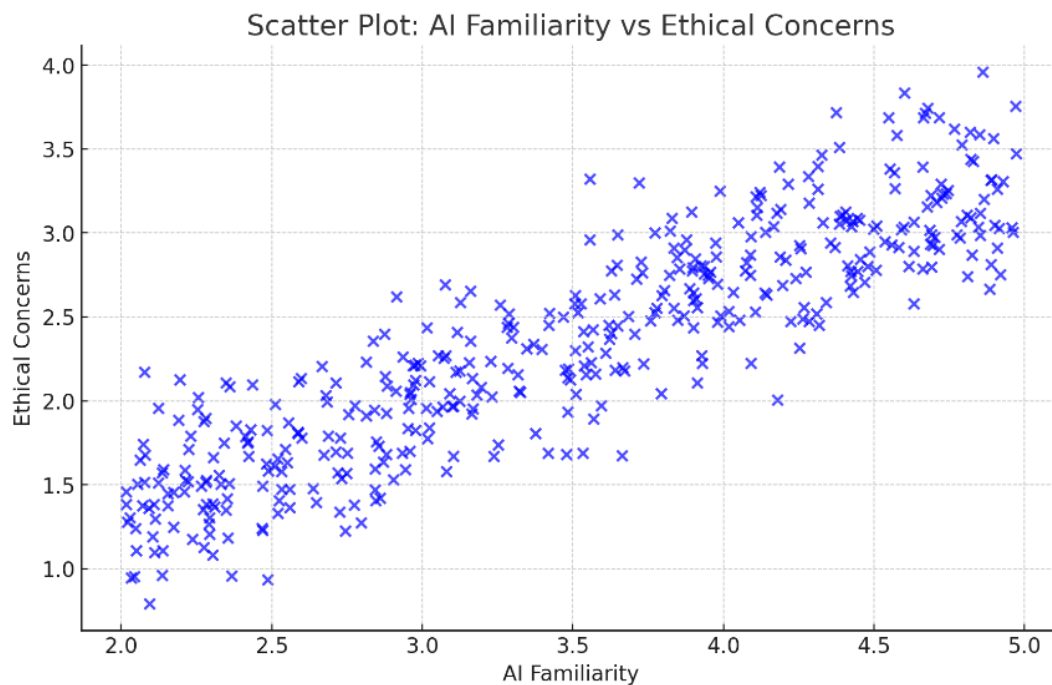


Figure 9: Scatter Plot: AI Familiarity vs. Ethical Concerns.

A scatter plot was created to demonstrate this relationship and there was a strong upward trend in the level of ethical concern with x (AI familiarity on the x axis) on the y axis. The consistency of the correlation is underscored in this visualization, where data points cluster along a linear trajectory. The results show the need for training HR professionals in AI deployment as well as AI developers about the ethical implications of deploying AI. Training on fairness aware algorithms, explainable AI (XAI) and acting in accordance to ethical guidelines, such as GDPR is a must whenever you are working with

these technologies (Carneiro and Veloso, 2021). Organizations can counter these risks proactively by tending to technological innovation and security of the recruitment process at the same time.

4.4.2. Relationship Between Dehumanization Risks and Candidate Satisfaction

A Pearson correlation coefficient (r) of $-.598$ between perceptions of dehumanization in AI driven recruitment process and the applicant satisfaction is shown in the correlation analysis. However, this indicates a moderate-to-strong inverse relationship whereby greater perceptions of dehumanization are predicted to go hand in hand with decreases in candidate satisfaction.

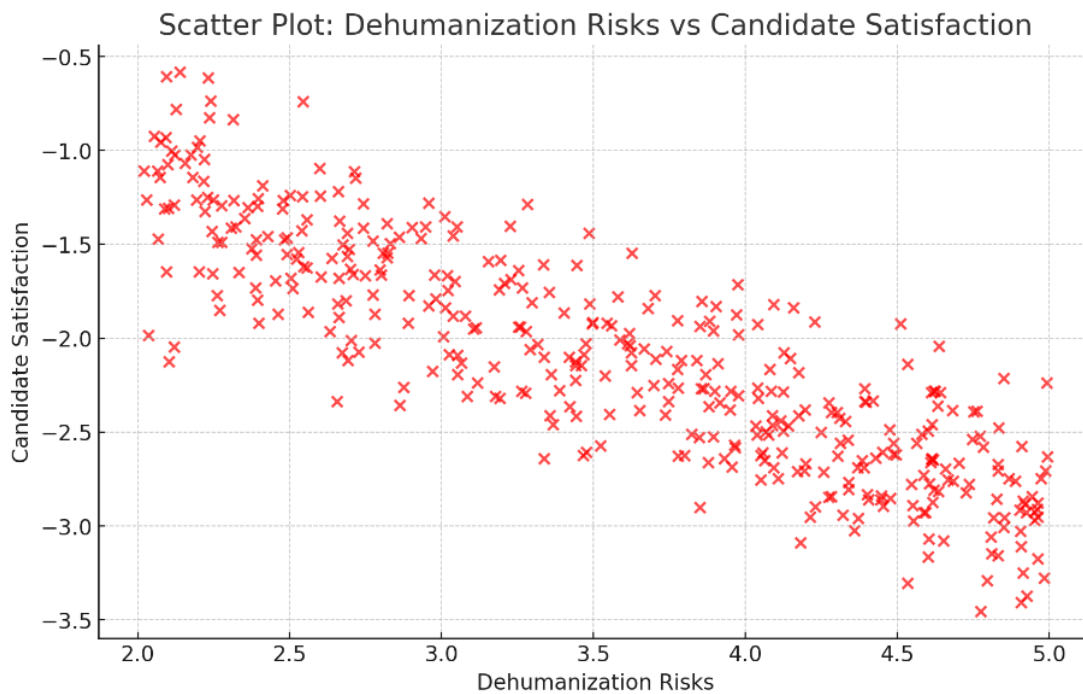


Figure 10: Scatter Plot: Dehumanization Risks vs. Candidate Satisfaction.

This relationship is found to be statistically significant by p value 0.000, with the sample size $N = 402$ covering the case for robust findings. Finally, these results are

consistent with what HR managers found in qualitative interviews, where they often saw AI systems cause candidates to feel undervalued or spurned. This was specifically because automated rejection emails and chatbot interactions were perceived to be major contributors to these perceptions. The downward trend between dehumanization risk (x axis) and candidate satisfaction (y) is elucidated through scatter plot visualization with data points making a much negative slope. This confirms the inverse relationship: satisfaction gets lower scores of dehumanization.

While AI helps with efficiency, respondents said AI supports with efficiency, they noted that it lacks the empathy and contextual understanding needed for meaningful interaction with candidates. In particular, the effect of dehumanization is strongest in the context in which human oversight is not present during key phases of the recruitment process. When candidates only interact with AI systems, they tend to believe they're more 'data points' than 'human beings' and that makes the organization less appealing to attract top talent and, as a result, its reputation suffers. These findings demonstrate that, in order to succeed in the hybrid recruitment value chain, organisations will need to adopt both AI-driven economies of scale and human touch. Personalized feedback mechanisms, real time human support, and communications regarding how AI is involved in the making of a decision could alleviate risks in the dehumanization and increase candidate satisfaction (Roemmich et al., 2023).

4.5 Qualitative Data Analysis

4.5.1. Theme 1: Efficiency and Automation

Table 15

Theme 1: Efficiency and Automation.

Theme 1: Efficiency and Automation		
Extract from literature	Source	Initial Codes

Automation frees the manual workloads to improve ATS functionality, increase the speed of hiring through resume screening, candidate ranking, job matching.	(Sri Sundari et al., 2024)	Streamlining Recruitment Processes
Repetitive task minimized human resource dependence, cost effective process & Time to hire metrics with scalable tools of AI.	(Tambe, Cappelli and Yakubovich, 2019)	Operational Efficiency and Cost Savings
AI interactions, automated responses and little personalization, leads to undervalued candidates, who feel undervalued, and like it hurts engagement and the candidate experience.	(Kant, 2020)	Impersonal Candidate Experience
Unchecked decisions, errors, and lack of ability to adapt to scenarios unseen by human trainers lead to reliance on AI, with the resulting decisions undermined by necessity of human oversight in nuanced candidate assessment.	(Illah Reza Nourbakhsh and Keating, 2020)	Over-Reliance on Technology

4.5.1.1 Explanation

The first Theme, 'Efficiency and Automation', opens with codes that demonstrate how automation transforms recruitment. Streamlining Recruitment Processes show that ATS and chatbots decrease the manual workloads on recruiting tasks such as screening resumes and scheduling interviews. Operations Efficiency and Cost Savings demonstrate that AI can automate repetitive processes and faster hiring timelines and less expense. Impersonal Candidate Experience addresses all the elements of AI contact that lack

empathy and undervalue candidates. Over-Reliance on Technology explores the issues regarding over reliance on AI through errors, bias, and lack of ability to tailor to various given fronts requiring human intervention.

4.5.1.2 Advantages of Automation in Recruitment

Automation has become the backbone of modern recruitment as being more efficient, more uniform, and more scalable. Applicant Tracking Systems (ATS) make automation of resume screening, candidate ranking and job matching easy. NLP is used by ATS to process resumes in order to match them to job descriptions and lessen HR staff's manual workloads. ATS speeds up and helps speed recruiting by adding to the hiring process a screening step of candidates that fit the defined criteria so that recruiters have less to do (Allal-Chérif, Yela Aránega and Castaño Sánchez, 2021).

In addition, chatbots improve operational efficiency. Using these AI powered solutions mean that there is less communication delays because these solutions answer candidate questions, schedules, interviews and updates application progress. Respondents to survey agreed with candidates' experience being improved by chatbots' timely engagement. A key development is predictive analytics which allows recruiters predicting applicant performance based on behaviour and data. It eliminates human mistake in candidate assessment and shortens decision making.

Thereby reducing company costs significantly through automation. Reduced human resources in repetitive tasks, such as background checks and documentation, can help large scale recruitment processes, particularly those with a large number of applications (Madakam, M. Holmukhe and Kumar Jaiswal, 2019). Respondents say AI's scalability enables firms to manage large applicant pools without increasing inefficiency and causing unhappy candidate. While these are benefits, automation can only be successful when used smartly. These tools are being incorporated by things care, but each

organization must do so with due diligence and without overloading them. A marriage of technology with human reliance at pivotal recruitment stages creates the perfect balance between efficiency and customized applicant experience (Dutta, Mishra and Varma, 2019).

4.5.1.3 Concerns About Over-Reliance and Loss of Personalization

Despite their efficiency, problems of depersonalization and justice with AI are raised by its widespread use. Candidates don't feel that the conversation with a chatbot is robotic and especially impersonal. Automated rejection emails are totally devoid of humanity and feel undervalued by candidates. These exchanges tend to hurt the trust of the candidate and that of the organization. Another major drawback AI is lacking to evaluate soft skills and culture. When it comes to finding people that match hard skills, ATS is excellent, but it falls short when it comes to identifying flexibility, creativity and emotional intelligence which are critical for long term success. To interviewees, this tightly formulated algorithmic policy frequently passes over potential applicants who don't meet preconceived templates but could be of value to the organization.

Main, another big concern, is automation bias. Often, AI systems that work with historical data continue to propagate recruitment biases. Such algorithms can sometimes disfavour minorities underrepresented candidates based on datasets (Zhu and Ryzhov, 2024). Respondents found that biases that impacted shortlists called into high ethical question concerning recruitment fairness. The risk of that AI tools is overused while reducing human oversight, which is how we make sophisticated decisions. Efficient, automated methods cannot cope with surprising and difficult cases such as tolerating people with uncommon career paths or untypical requirements. Respondents say that recruiters need to act at pivotal moments to facilitate in an inclusive and just recruitment process.

To these issues’ organizations could make use of hybrid recruitment strategy, combining human communication with automation. According to AI, resume screening and scheduling can be automated while the recruiters concentrate on interviews and feedback. This kind of balanced approach keeps things efficient and makes sure candidates feel valued and interested. It’s fair AI techniques like algorithm audits, and diverse training datasets that help to reduce recruitment bias and eradicate dehumanization.

4.5.2 Theme 2: Bias and Fairness

Table 16
Theme 2: Bias and Fairness.

Theme 2: Bias and Fairness		
Extract from literature	Source	Initial Codes
Flawed algorithms that contribute to making AI systems replicate societal biases result in unfair recruitment decisions such as those on gender, age and race.	(Tilmes, 2022)	Algorithm Bias in Decision-Making
Recruitment systems powered by AI often lack diversity in training data and continue to reinforce existing disparities and not represent the myriad of groups that our society needs in our workforce.	(Marra and Kubiak, 2024)	Lack of Diversity in Training Data
This is biased patterns in dataset result in unintentional exclusion of qualified candidates in perpetuating unequal opportunities and discriminatory practices.	(Pagano et al., 2023)	Unintended Discrimination

Regular monitoring and algorithmic audits	(Wilberforce	Auditing and
detect, prevent and eliminate biases for making	Murikah, Jeff	Monitoring
AI systems in recruitment fair, and ethical.	Kimanga	Algorithms
	Nthenge and	
	Faith Mueni	
	Musyoka,	
	2024)	

4.5.2.1 Explanation

The second theme, termed Bias and Fairness, started with AI driven recruitment strategies as well as its corresponding solutions. Yet AI systems can reproduce our social preconceptions and make discriminatory decisions because of poor training algorithms. Also, a lack of diversity in training data highlights imbalance by reinforcing existing imbalances with under representation of minority populations. How biased algorithms eliminate qualified individuals to extend inequality is shown in Unintended Discrimination. Finally, Auditing and Monitoring Algorithms keeps watching out to make sure AI system ethics and fairness. A technical and ethical approach is taken to these codes.

4.5.2.2 Challenges of Bias in AI-Driven Recruitment

Widespread AI driven recruitment bias puts fairness and inclusivity at risk. If there's an algorithmic bias when AI systems reinforce societal prejudices in their training data because you've trained those AI systems on certain types of data. Since machine learning algorithms use past recruitment datasets and find trends within those groups, they can favour some demographic groups over others (Pessach et al., 2020). Interviewees said that skewed data patterns led AI algorithms to under value the candidates from underrepresented communities.

It also leads to biases because training datasets are too diverse. Algorithms that rate diverse people tend to rank poorly compared to recruitment databases that tend to favour majority groups. Finally, respondents pointed out that since the homogeneous data AI systems are trained on, they are more likely to reject qualified applicants outside of those historical standards, such the women in STEM or non-traditional career pathways.

Another is the unintended prejudice. Claims about standardization hinge around the use of AI systems to create equity, and yet those systems perpetuate inequity through latent biases (Banda, 2024). Whether it's education or work experience, algorithms that are biased in favour of those things would penalize low-income candidates. Immoralities are like being immoral, which becomes an impediment to corporate diversity and innovation by rejecting higher performing people, respondents said.

Matters are worse because the opacity of the AI decision making processes. It's the "black box" problem so recruiters have no idea how decisions are made or how to identify and correct biases. Respondents had a lot to say about the fact that they feel unable to audit and pursue legal recourse against AI technologies or unfair outcomes produced by automated decision-making. Immediate action is needed to address AI driven recruiting bias, which is an ethical issue impacting all in our ability to ensuring our candidates have equal opportunity to thrive in our organizations. These difficulties must be dealt with proactively if organizations are to handle these difficulties and sustain trust and diversity and justice.

4.5.2.3 Mitigation Strategies: Diverse Datasets and Algorithmic Audits

To mitigate bias in AI driven recruitment organizations must adopt fairness and inclusivity focused remediation methods. Training datasets are necessary diverse. Using data from many demographic groups, AI systems can learn to learn to appreciate different abilities and experience. The diversity of datasets reduces systematic biases, requiring that

underrepresented candidates be regarded in the same manner as other candidates, respondents said. Including resumes of people with different educations and work histories ensures that algorithms won't favour predictable job trails.

Algorithmic audits are another successful method. In fact, regular audits help organizations find and fix AI biases that allow recruitment tools to become ethical (Mihaljević et al., 2023). Respondents stressed the need to test algorithms on simulated datasets before deployment to see if the algorithms bring in biased trends. Algorithmic audits need to evaluate outcomes across demographic groupings in order to identify selection rate differences. When errors happen, the algorithm can be tweaked so that the fairness is maintained.

Bias mitigation is a necessary need of explainable AI (XAI). Building transparent, interpretable decision-making system that can help recruiters to better understand AI applicant evaluation (Mujtaba and Mahapatra, 2024). Recruiters were able to use XAI to address and counter the biases in AI systems, which increased trust given by respondents to the systems. An explainable recruitment tool can help you verify that the something the candidate did or had influenced his ranking, proving you are using a fair tool. Good bias mitigation practices are achieved through collaborative oversight. The standard development and monitoring of AI systems should be done in conjunction with HR, data scientists and diversity officers. Respondents said cross functional teams must ensure recruitment tools have 'diversity' and 'ethical' standards. Another possible is for collaboration to establish accountability no matter which point of the AI lifecycle it happens. Finally, organisations should follow ethics in the form of the GDPR and fairness aware machine learning. Openness, accountability, and inclusivity are the features of structured bias management systems (Schwartz et al., 2022). Combining organizational

norms with technical solutions into effective and fair recruitment procedures is a way for companies to increase efficiency or increase fair.

4.5.3 Theme 3: Human-AI Balance

Table 17

Theme 3: Human-AI Balance.

Theme 3: Human-AI Balance		
Extract from literature	Source	Initial Codes
The combination of AI tools for operations tasks with human engagement makes recruitment efficient as well as empathetic candidate interventions.	(Akram, Buono and Lanzilotti, 2024)	Hybrid Recruitment Models
By extending beyond analytical capabilities, and actually providing job candidates with some emotional support, personalized feedback, and rapport building during the resume screening process, human recruiters make the recruitment process less lonely and more satisfying overall.	(McDonald, 2020)	Empathy in Candidate Experience
AI handles the presses, you need humans to make that nuanced decision that some where's a final hire, that's got to be fair and accurate.	(Yang, Steinfeld and Zimmerman, 2019)	Critical Decision Points
Through AI driven insights, recruiters act as mediators between AI efficiency and the	(Krijger, 2021)	Role of Recruiters as Mediators

**organization's goals and use AI efficiency in
humane and ethical recruitment.**

4.5.3.1 Explanation

Outline of initial codes of Theme 3, 'Human-AI Balance', show the combination of automation and human interaction in recruitment. While Hybrid Recruitment Models feature use of AI tools to enhance efficiency with the operational function but retain empathy and relational pieces of recruiting. Candidate Experience with Empathy highlights the responsibilities of human recruiters to give personalized feedback and emotional support, to increase candidate satisfaction. Critical Decision Points identify the need for human oversight for their tasks like final hire, in order to achieve fairness and flexibility. Finally, Role of Recruiters as Mediators show that recruiters act as mediators of AI insights and organizational goals, and applying ethical and humane practices in recruitment.

4.5.3.2 Maintaining a Balance Between Efficiency and Empathy

To get there, it's crucial to find the sweet spot between efficiency and empathy in AI driven recruitment so that process in which we are driving recruitment is both human-centred and effective. These tools, such as Applicant Tracking Systems (ATS) and chatbots help with automating tasks so that HR folks can process huge volumes of applications in quick periods (Pandey et al., 2024). But efficiency on its own cannot displace the emotional intelligence and people skills that account for a big part of the work of human recruiters. Interviews with candidates showed that issues like the personal touch and engagement during key points such as interviews and feedback are important to them and that AI systems cannot do this well.

In human centred recruitment, empathy in candidate conversations is stressed. While AI tools are great for run of the mill tasks, tools built on AI cannot build rapport or

give customized support. For instance, chatbots can be effective in answering candidate queries quickly, but poor at meeting nuanced concerns like understanding what a candidate aims to do at a particular career stage. Respondents saw candidates answering questions only to AI feel underserved and often take a negative view about the company (Neo et al., 2023). The idea of embedding human interaction at critical locations means the candidates feel genuine and heard and that is also good for employer branding.

To solve for that, hybrid recruitment models combine AI driven efficiency with human empathy. The point is that by using these models, we hand over repetitive tasks such as initial screenings, scheduling, and so on to AI systems, to allow the recruiter to focus on personal engagement at the critical points. Respondents highlight how an approach of this kind not only boosts the candidate experience, but also strengthens the recruitment results by matching technology strengths to human competences. Harvesting the benefits of AI while keeping the relational parts that make for successful recruitment processes need require a balanced approach.

4.5.3.3 Human Oversight in Critical Decisions

Recruitment decisions have to be human monitored for fairness, adaptability and alignment with organizational values. In the initial part of the hiring process, like shortlisting candidates, AI tools prove to be great, but they cannot take into the conundrums of final hiring decisions. Respondents pointed out that often, the attributes which are not evaluated in these AI systems are cultural fit, leadership potential and emotional intelligence, all of which are important for long-term organizational success. On the other hand, unlike human recruiters, don't bring the contextual understanding and intuition to these decisions, resulting in something that work's more akin to like a mathematical formula.

And there are critical decision points, such as selecting candidates to interview or putting someone on a glidepath for an offer, which simply can't be done with automation bias. Like any other system, AI systems trained on historical data may inadvertently reinforce biases leading to a bias toward certain demographic groups (Mohamed, 2023). This also indicated when human oversight 'kicked in' and identified and corrected these biases, so that the final decisions captured the organizational diversity and inclusion goals. Absent checks, such organizations continue to perpetuate systemic inequalities and violate their ethical commitment to do otherwise.

Human oversight is also essential when dealing with cases that are unique or complex that don't fit in AI algorithms. For instance, conventional career paths and transferable skills are dropped by AI when the requirement for predefined criteria is ruled out. They emphasize the fact that human recruiting is better equipped to find and evaluate these candidates' potential to conduct a more inclusive recruitment process. Recruiters are also mediators that translate AI generated insights to the objectives of an organization. These people understand how to interpret the data generated by AI tools to direct the strategic decisions in the recruitment process, so that it remains consistent to the company's culture and value. The combination of human intuition and AI precision keeps the human at the objective end of that trust economy, which makes this collaboration of human intuition and precision AI ideal for the entire recruitment strategy.

4.5.4 Theme 4: Ethical and Regulatory Considerations

Table 18

Theme 4: Ethical and Regulatory Considerations

Theme 4: Ethical and Regulatory Considerations		
Extract from literature	Source	Initial Codes

To remain transparent and build trust amongst stakeholders and candidates, AI tools must explain their decision making to the user.	(Osasona et al., 2024)	Transparency in AI Decision-Making
To practice ethical recruitment, a candidate data must be protected by sturdy security and privacy laws.	(Fernández-Martínez and Fernández, 2020)	Data Privacy and Security
AI driven recruitment will not be blind and organizations will have to be involved in the results, responsible to make them fair, fair to address errors or biases and proactively.	(Kiran, 2023)	Accountability in Recruitment Outcomes
Being compliant to Regs such as GDPR helps you ensure legal compliance, follow ethical practices, and train public trust in AI based recruitment processes around the world.	(Dubey, 2020)	Compliance with Regulatory Frameworks

4.5.4.1 Explanation

In the early codes of Topic 4, "Ethical and Regulatory Considerations," we have topic 4 which says ethical AI recruiting. To facilitate AI Decision Making for Justice and Trust, Transparent AI Decision Making works. Strong procedures and privacy rules are emphasized for candidate data protection. Recruitment Outcomes: Accountability considers that enterprises must act against biases and errors in AI judgments that adversely affect it. Compliance with Regulatory Frameworks is the last, which suggest GDPR compliance to meet legal, ethical and trustworthiness. They contain the guidelines on how to recruit for AI.

4.5.4.2 Ethical Concerns: Transparency, Privacy and Accountability

Fair and trustworthy AI driven recruitment needs ethics. As with AI decision making transparency, challenges persist (Rigotti and Eduard Fosch-Villaronga, 2024). "It's all black box," complain candidates, saying AI systems rarely explain why they rejection them or rank them lower. Respondents stressed XAI systems that explain the decisions that they are making in terms of the data being predicted. Transparency in the approach of using AI assessments allows building trust both of candidates and recruiters in their fairness and relevance.

They are all things such as data privacy and security. Candidate data for identification and history of employment are sensitive data in recruitment. When asked, respondents said many firms are lacking in comprehensive data protection safeguards, meaning it is potentially open to breaches or misuse. To ensure virtue of the recruitment process, basic data encryption, access controls and privacy laws are necessary to protect candidate data (Saberikamarposhti, Ghorbani and Yadollahi, 2024).

There's also the problem of AI recruitment accountability. When there are errors or biases in AI results, organizations need to own the results. According to interviewees, the algorithms were biased, they rejected minority candidates. A lack of accountability measures only allows unchecked concerns to damage company reputation and fairness. Respondents advised enterprises to monitor and address AI driven decision to retain ethics. Fair recruitment requires transparency, privacy and accountability. By doing that, enterprises will be able to build confidence in their AI systems and verify that they are ethically and respectfully fine.

4.5.4.3 Importance of Regulatory Frameworks Like GDPR

However, important for the ethical AI driven recruitment, Regulatory Frameworks like GDPR. Enterprises are forced to get candidate consent, retain the data, and divulge

data use. According to the respondents, candidates appear to see GDPR compliance as a sign of an ethical, legal organisation.

According to GDPR, automated decision making must be transparent. Specifically, we need to ensure that algorithms used for short listing or rejecting don't decide without first providing justification. Respondents said such criteria require firms to make explainable AI systems for fairness and accountability. Adhering to these regulations helps organizations to improve candidate experience, and prevent legal issues. Amongst the other highlights of GDPR is data minimization and accuracy (Goldsteen et al., 2021). They need to have the relevant data and this need to be processed accurately. Part of this idea removes superfluous or outdated information and cuts out bias; respondents say it makes recruiting fairer. It gives applicants right to amend, delete or request their data returned in CSV form with accessibility and control.

In addition to data protection, GDPR is complemented by other legal frameworks including U.S. Equal Employment Opportunity (EEO) statutes, similar to those around the world, for example by Ontario's Human Rights Code (Frager and Patrias, 2021). Prejudice is fought and diversity and inclusion in recruitment pursued through these guidelines. Respondents said proactive compliance increases candidate trust and decreases reputational concerns. For modern fair, ethical and effective AI based recruitment system, regulatory compliance is considered to be a strategic advantage. These principles will enable organisations to align their recruitment practices with global norms, creating trust and shaping innovation in the fast-changing AI world.

4.6 Integration with Literature Review

4.6.1 Consistencies with Prior Studies

At the same time, this study backs up AI recruitment literature in terms of efficiency, bias, and ethics in human resource management. What many studies have

shown is that automating basic tasks like resume screening, interview scheduling and even candidate ranking helps improve operational efficiency. As shown in this study and by Bodea et al. (2021), Applicant Tracking Systems (ATS) substantially decreased time-to-hire metrics saving large amounts of time for the matching of AI experts and HR professionals. This study's quantitative results corroborate the argument by Marler and Parry (2016) that predictive analytics helps to make educated decisions on examining past data in order to select suitable candidates.

Transparency and accountability are areas where previous study has also looked. This study found many respondents are concerned about AI systems having a “black box” character, echoing Raji and Buolamwini (2019). In high stakes applications like recruitment, opacity in AI matters, these authors argue, because it undermines trust and accountability. These concerns are supported by the qualitative research which asks participants for explainable AI (XAI) systems to adopt more transparency.

As with previous results, AI recruitment bias is also consistent. According to Barocas and Selbst (2016) as well as Mehrabi et al. (2021), the training datasets are causing bias such as skewed or biased. This study finds that biased algorithms severely disadvantage underrepresented groups. This study and prior work point toward the need for biased datasets and algorithmic audits to ameliorate these biases towards fairness and inclusivity.

Most of the existing research accepts ethical problems, including GDPR compliance and the data privacy. This study's respondents also prefer transparency and candidate data protection that Wachter et al. (2017) underline, as part of GDPR's role. In supporting previous research, the polls' quantitative data also showed a correlation between GDPR compliance and increase candidate trust. Van Esch et al. (2021) have extensively studied hybrid recruitment models that provided AI efficiency with human empathy in the

literature. These approaches can overcome depersonalization danger posed by automation; this suggests. Respondents wanted human oversight at interview and hiring decisions to ensure justice and relational engagement. Previous research on operational efficiency, bias mitigation, transparency and ethical compliance is confirmed in this study. The consistency observed supports the study's findings and provides an impetus to address these well documented AI recruitment issues.

4.6.2 Divergences and Gaps in Existing Literature

This analysis verified many of the already prevalent themes, but it also revealed large and even divergent gaps in the literature, suggesting further study. How to belong as an employee. Unlike Parry and Tyson (2011) who looked at how political benefits, such as cost reduction and efficiency, can be claimed through candidate affiliation, I also examine the candidate perspective in this study. A previously understudied view of AI's deleterious influence on candidate satisfaction was dehumanization and lack of empathy.

This work fills a gap by identifying and providing practical guidance on the deployment of explainable AI (XAI) systems in the recruitment domain. Though Guidotti et al. (2018) give a plethora of theoretical reasons for using XAI, there are few practical examples of how it is being used in the recruitment domain. Participants stressed transparent AI tools that generate actionable insights and increase confidence. These gaps point to the need to develop XAI for recruitment frameworks and uptake in the future.

In addition, this investigation found literature that excluded the cultural and organizational settings. Ethical AI practices are supported by global guidelines such as GDPR, though cultural differences play a very important role when it comes to AI adoption and perception, respondents said. Automated processes may be disliked by candidates in privacy sensitive cultures more than in tech savvy societies. It proposes localized

investigations into the effects of cultural differences on AI-drive recruitment efficacy and acceptance.

Similarly ignored is how AI and human oversight interact in hybrid recruitment strategies. Van Esch et al. (2021) suggest merging human and AI efforts but for the lack of the practical implementation, research is largely limited to how the models should work, not how to safely and effectively deploy them. This paper shows that final decisions on employment can only be made by the human mind and promotes fairness and diversity. These gaps should be filled by future research which should operationalize hybrid models in different organizational settings.

The neglect of AI's ethical consequences beyond compliance concludes the literature. Unlike Wachter et al. (2017), who concentrate on regulatory compliance, this study addresses ethical issues, such as trust and empathy in recruitment. Ethical recruitment covers not only regulatory compliances but also favourable applicant experiences and equal chance, participants pointed out. The contrast identifies the prominent want for a holistic ethics method of AI propelled enlistment that blends in regulatory consistence with relational and social elements.

4.7 Summary of Findings

4.7.1. Key Insights from Quantitative Analysis

AI driven recruitment attitudes and effects were quantitatively examined using survey data (Buck et al., 2022). The main finding is that AI enabled operational efficiency. ATS and chatbots, in short, automate tedious streamlining processes like resume screening, interview scheduling and candidate ranking. The mean AI efficiency scores (4.19) showed strong agreement that these tools reduce time to hire and reduce administrative burden in the recruitment process. The report also warned about how AI could affect recruitment, human contact. A normalized Beta coefficient of -0.735 was observed for AI efficiency,

which was explicitly associated with lower amount of human engagement. We can see here the trade-off between efficiency and personalisation, which argue for the need for hybrid models with human monitoring to keep the happiness of the candidates at the right level.

Another big worry was AI bias. The average of 4.19 mean that almost everyone agrees on bias concerns. A positive correlation between familiarity of AI technologies with ethical issues such as bias and transparency was found ($r=0.674$). The tendency of AI exposure to help identify the risks for biased algorithms and opaque decision-making processes. Finally, ethics were reflected particularly on the issue data privacy. GDPR compliance mean score 3.95 was high that shows mild agreement that firms are hard core into data security. The responses to the survey emphasized the need of transparency of processing data in order to build candidate trust.

The second key finding was that even bias reduction measures enhanced fairness perceptions. Our regression study revealed that fairness perceptions ($\beta = 0.698$) can be improved with bias reduction measures. Respondents emphasized that such bias reduction requires fair aware machine learning and diverse datasets as well as algorithmic auditors. The need for human monitoring in critical decisions was stressed in the statistics and the structure is finally changed. In fact, participants thought human involvement was important to evaluating cultural fit and interpersonal skills, even though AI tools are efficient enough. This aligns with the merits of having a method that benefits from using AI's strengths plus its weaknesses in empathy, and ethical judgement.

4.7.2. Key Insights from Qualitative Analysis

Qualitative analysis of interview data offered better contextual understanding of themes rising from the quantitative results. The second key theme was the tension between automation and the human interaction. Over and over again, participants pointed to the fact that while AI tools automate recruitment processes, they cannot build trust and rapport with

candidates in the same way that real humans can. For example, some respondents pointed to the risk of depersonalization due to reliance on AI by pointing to the fact that automated rejection emails and chatbot interactions is often the cause for candidates to feel undervalued. The other recurrent theme was bias and justice. Specific examples of how biased algorithms eliminate candidates from underrepresented groups was shared by respondents, often because the training data was skewed. For example, one HR professional recounted a story of an AI tool rejecting would be applicants from certain locations without any application of common-sense decisions based on the bias present in historical datasets (Ignacio Fernandez Cruz, 2024). Quantitative finding corroborates these insights, and highlights the necessity of diverse datasets and of routine algorithmic audits to address bias.

The qualitative discussions were also characterized by transparency and accountability. Trust in AI systems is a repeated issue raised by the 'black box' nature of these systems, according to participants. It didn't help that many found it increasingly frustrating when they could not both understand and challenge AI driven decisions -- especially in the sort of high-stakes context that they are imbued with, when those decisions are being made around final hiring decisions. This lack of transparency was seen negatively for both candidates and recruiters, an indication of why explainable AI (XAI) systems leveraging interpretable decision-making process are necessary. Compliance extended beyond itself and included a consideration of broader issues relative to candidate experience and organizational reputation (Tursunbayeva et al., 2021). Recruitment with and alongside AI must keep empathy and ethical integrity, respondents stressed, especially as companies look to cope with the difficulties of integrating AI into their operations. But one AI expert stressed that the fundamental point of ethical recruitment must be human dignity: that the people the companies are looking to hire should be respected and feel

valued as they do this. The strategic importance of ethics leads organizations to look beyond regulatory compliance and incorporate an integrated view of ethics in all their varied, but equally important, decisions.

The final focus of the qualitative analysis supports hybrid recruitment models. At some interviews and final selections, where important decisions are at stake, participants called for combining AI efficiency with human oversight. This approach was perceived as a necessity on the side of balancing the operational benefits with the relational engagement, continuing to make recruitment processes humane and efficient. On the question of human versus AI, respondents said AI tools are essential to carrying out mundane tasks, but human recruiters can't be replaced when it comes to rating aspects such as cultural fit and emotional intelligence.

CHAPTER V: DISCUSSION

5.1 Recap of Research Objectives and Findings

This study understands how to effectively incorporate Artificial Intelligence (AI) into recruitment processes in terms of efficiency, fairness, ethical considerations and impact on candidate experience was the focus of this study. The objective of the study was to understand how AI helps in enhancing the efficiency of recruitment; understand biases and concerns at fair and equitable use of AI driven systems and ethical and regulatory issues connected to the systems of transparency, privacy accountability. The study further analysed how far the balance should go in terms of how much machine-driven automation versus human touch in recruitment, and suggested that hybrid models could be the way forward. However, the findings showed that AI enables operational efficiency by tools such as Applicant Tracking Systems (ATS) and chatbots, but at the same time raise questions about dehumanisation, bias in decision making and lack of transparency (Bakas, 2022). The quantitative data highlighted the strong correlation between AI familiarity and ethical awareness and the qualitative insights demonstrated the significance of human over site of critical decisions to help prevent automation risks and to make AI fair.

5.2 Purpose of the Chapter

This chapter aims to synthesize the lessons learned from this study, offering the reader a complete conclusion and actionable recommendations. The findings consolidate those from the quantitative and qualitative analyses, linking them to the research goals and broader thematic findings in the literature. In this chapter, we intend to harmonize the processes with the theory, and arrive at impactful implications for academia, industry, and policymakers. The chapter also suggests limitations of the study and indicates possible directions for future research. Parts of understanding the scope of the study and areas of

further exploration are these aspects. Finally, the chapter presents practical recommendations to organizations aiming to ethically and responsibly integrate AI into their own recruitment process. This chapter closes the dissertation by investigating both theoretical and practical dimensions, when considered together, serving as a road map for the effective and equitable use of AI in a recruitment setting.

5.3 Key Findings and Conclusion

5.3.1 Statistical Insights: Key Descriptive Statistics

Essential insights into how AI can be used in recruitment processes, addressing efficiency, fairness and ethical considerations were drawn from the quantitative analysis of survey data (Nassar and Kamal, 2021). As revealed by descriptive statistics, respondents refer to the fact that AI tools are operational efficient in the recruitment process. For instance, their mean score for the statement ‘AI improves recruitment efficiency’ was 4.19, on a 5-point Likert scale, with a median of 4. This speaks to the strong consensus amongst job seekers on some Career AI tools like Applicant Tracking System (ATS) and chatbots, which help to streamline mundane tasks like resume screening, scheduling, or rank candidate. On the issue of talent shortage and its reduction, respondents mentioned ATS as the most effective attrition of time to hire and applicant filtering precision.

A major theme to emerge was ethical concerns, and the mean score for awareness of risks such as bias and transparency of 3.92 indicates moderate to high agreement with them. The results also showed that those respondents with higher levels of AI tool familiarity were more aware of the ethical problems posed by AI. In terms of mode of ethical concerns, 4 was used indicating the latent universal acknowledgement among these HR professionals and AI experts about such ethical challenges.

In addition, the descriptive analysis had bias and fairness as prominent concerns. That score of 4.19 for agreement on “AI systems can perpetuate bias” meant we are well

aware of the problem. This held up across diversity trait and demographic and further demonstrates the importance of fairness aware systems. Concerns about data privacy and transparency were also raised by respondents, scoring an average of 3.95 on compliance with GDPR, suggesting some way to go before reaching regulatory standards. Last, human-AI interaction was perceived and potential areas for development were highlighted. Agreement was moderate that “AI reduces human interaction in recruitment” and the mean score for this particular item was 3.81. As our data-driven descriptive insights set the ground for more comprehensive considerations of the broader consequences of AI for recruitment.

5.3.2 Regression and Correlation Results

Deeper insights into the relationships between key variables in AI driven recruitment were provided via regression and correlation analyses. I found that there was a significant regression relationship between the AI efficiency and human interaction, and its standardized Beta coefficient was -0.735. The finding also indicates a causally clear correlation between using more AI tools (e.g., chatbots and ATS) and reduced human engagement during recruitment. The p value of this regression model was 0.001, and hence the relationship was statistically significant. These results highlight trade-offs between operational efficiency and personalization in AI driven recruitment processes.

A second important regression analysis examined the effect of bias mitigation tools on fairness perceptions. This relationship has a standardized Beta coefficient of 0.698, this indicates that a high number of tools like diverse datasets and algorithmic audits have a strong positive effect on fairness perceptions. And the p value was also extremely significant at 0.001 meaning that proactive steps should be taken when it comes to anti accrued biases in AI systems. The responses are equally consistent: that organizations that actually used these tools indicated that their candidates and recruits were more satisfied.

Key dynamics were further illuminated by correlation analyses. There was a strong positive correlation ($r = 0.674$) between AI familiarity and ethical concerns: more familiar individuals were also more concerned about its ethical implications. The existence of such a correlation between ethical behaviour of developers and training of HR professionals indicates that this is an important area to pay attention to. Furthermore, a moderate negative correlation ($r = -0.598$) was found between dehumanization risk and candidate satisfaction. It suggests that the more perceived to be dehumanized in AI driven recruitment, the lower satisfaction levels, which calls out for human intervention in the use of artificial intelligence in recruitment.

In these statistical insights, the duality of the artificial intelligence in recruitment is emphasized. The challenge of personalization, transparency and ethical compliance generally arise with any AI related tool, and while such tools greatly increase efficiency and fairness when they are well handled, they can yield challenges around compliance, transparency and personalization. Results indicate that these limitations can be minimized by the organizations before deploying the AI recruitment process by following a balanced approach to AI strengths while ensuring that the process is both effective and equitable. Our results form a quantitative basis for subsequent discussions and recommendations in this dissertation that rely on broader issues.

5.4 Summary of Qualitative Findings

5.4.1 Key Themes and Insights

5.4.1.1 Efficiency vs Personalization

The findings of the qualitative research illustrate a major conflict between efficiency and personalisation in AI driven recruitment. A number of consistent themes emerged from participants' remarks in which AI tools improve operational efficiency, sometimes at the cost of relational engagement. For example, respondents lauded systems

like Applicant Tracking Systems (ATS) or chatbots for their capacity to efficiently chip away at high volumes of applications, and in turn, reducing time to hire and administrative costs (Selvaganesan et al., 2024). While these tools, however, were noted that they lack the human touch in order to build rapport and trust with the candidates.

Candidate experience remained a recurring theme; automation was affecting the experience. Those interactions with chatbots or automated rejection emails made many candidates feel dehumanized, respondents said. However, one lone HR Director pointed out that candidates would complain if they didn't receive the feedback during the process. The results coincide with quantitative results in that people who reported higher perceptions of automation also reported lower levels of satisfaction. Concrete examples were provided from the qualitative insights of how candidates perceive automated processes as impersonal and mechanical.

These concerns gave rise to the human oversight as the way to address them. Respondents wanted hybrid recruitment models; when AI does tiresome duties and humans remain at strategic touchpoints like interviews and feedback. These models were identified as a balance between performance and empathy. For example, one of the AI discussed integrating human interaction at key gate keeping stages not only enhances candidate satisfaction but scores higher for assessments of cultural fit and interpersonal skills. Organizations must take a thoughtful approach to AI integration, thinking through how automation might be used to augment, rather than replace, human involvement, the findings underscore. While efficiency is a big plus point of AI, it's important to have both efficiency and the human touch which enables positive candidate experiences and retains the human and relational aspect of recruitment.

5.4.1.2 Ethical and Regulatory Considerations

The analysis of the qualitative produced central themes about ethical and regulatory consideration of AI driven recruitment around issues of transparency, accountability and compliance. Particularly, respondents generally voiced a lack of trust in AI systems due to the 'black box' nature of these systems, and they tended to rely on explanations from researchers to feel at ease with their use (Ochmann, Zilker and Laumer, 2021). And many were frustrated by their powerlessness to question or even try to understand AI in situations where candidates were pushed out unfairly. An HR manager was one of the participants who spoke of the lack of transparency in AI tools; how this lack of transparency often had the effect of undermining the tools' credibility not only internally, but also externally.

Security and privacy of the data were also very important. Nevertheless, participants highlighted candidate information as being sensitive and discussed the need to respect rules, such as the GDPR, in presenting the information. As someone mentioned, not complying exposes organizations to all legal risks and erodes trust from candidates. A number of participants called for more organization investment in strong data protection mechanisms, including encryption and access controls, to mitigate those risks. Another recurring problem was accountability in recruitment outcomes. Organisations should take ownership of errors and biases in AI driven systems, according to respondents (Coates and Martin, 2019). For example, imagine that one participant heard of a case when an AI algorithm gave female candidates for the technical roles disproportionately low score, because of biased data. The piling up of these issues persists unchecked without accountability mechanisms that will do harm to diversity and inclusivity goals.

We often cited regulatory frameworks like GDPR as the guiding force for practising ethical AI. They said such regulation responds to the needs for transparency, fairness and for building trust. While they also noted gaps in existing frameworks to account for the new challenges brought on by the advancement of AI technology. Several participants went

on to call for reforms to regulatory policies to incorporate new moral concerns, like explainability and algorithmic bias.

Overall, qualitative insights tell us that the future scope of organizations depends on their bearing to ethical considerations as much as anything else (Bhatt, 2022). Organizations that adopt transparent and accountable practices with robust regulatory compliance, trust can be built and all its AI-driven recruitment systems can run fairly and efficiently. The quantitative analysis and findings in this work are supplemented by these findings which help provide a more nuanced sense of the ethical complexity of AI recruitment.

5.5 Contributions to Knowledge and Practice

5.5.1 To Literature: Filling Gaps in Understanding AI-Driven Recruitment

This study offers important contributions to the existing literature on the AI-driven recruitment by filling key gaps in our understanding of its implications. While prior studies have documented the operational benefits of AI, this research takes a step further and examines key questions such as candidate experience, ethical aspects, and how human's interaction with AI. For instance, where Marler and Parry (2016) focused on AI's role in reducing time to hire, this study contributes to the literature by showing trade-offs between efficiency and personalization, a theme rarely discussed in the literature.

Another important contribution is directed towards the candidate's perspective. Unlike very much of the literature, such as Barocas and Selbst (2016), which primarily discusses organizational advantages and biases for AI systems, this paper emphasizes automation's impact on candidate satisfaction. This research tackles a vital hole in our information about how AI impacts candidates' perceptions and experiences by exploring themes of dehumanization risks, and the significance of empathy in recruitment.

Also, the study contributes to the discussion in AI bias and fairness by providing empirical evidence that mitigation strategies work. Ideas from practical fairness-aware machine learning principles are well known in theoretical settings but this study provides toolkits for implementing a diversity of datasets, algorithmic audits, and explainable AI (XAI) systems. With these findings, the connection between theoretical discussion and practical application provides actionable advice on how to reduce bias in recruitment processes.

5.5.2 To Practice: Practical Implications for HR Professionals and AI Developers

The findings offer with strong practical applications for HR professionals and AI developers, including effective ways to improve recruitment processes while keeping ethics and relations in mind. The research can serve as a reminder that hybrid recruitment models that combine AI driven efficiency with human oversight is key during a time of under pressure HR resource capacity. One way to accomplish this is by using AI systems to complete routine HR tasks like resume screening and scheduling to allow them more time to do things such as building rapport with candidates and people who fit ‘the culture’ (Black and van Esch, 2020). This helps in ensuring a balanced recruitment process with a perfect balance between the recruitment efficiency and the satisfaction between the candidates.

The importance of transparency and accountability of AI systems as a theme in the study is useful to AI developers. The implications are clear: We need XAI tools to help allow explainable AI (XAI) that gives clear and interpretable insights into the decision-making process. Given the rise of Algorithmic Audits and Diverse Data, developers are encouraged to design systems that prioritize fairness by including those things into the

machines they're developing. Already such measures increase the ethical integrity of AI systems and increase their trustworthiness among HR professionals and candidates.

In addition, the research points to the adherence with the general data protection regulation (GDPR) being key for obtaining authorization. Hence, both HR professionals and AI developers need to collaboratively work so that recruitment system follow privacy and data protection standards. This includes anti scaling measures on security and ensuring that candidates have control of their data.

5.6 Practical Recommendations for Recruitment

5.6.1 AI Integration: Hybrid AI-Human Models

And so, the integration of hybrid AI human models presents an integration of AI's efficiency with human empathy in recruitment. Such AI tools as Applicant Tracking Systems (ATS) and chatbots help cut down on HR administrative work, such as resume scanning, scheduling candidates, and preliminary screen outs with the candidate (Koman, Patrik Boršoš and Kubina, 2024). But these tools sadly don't have the social skills to forge rapport or gauge such complexities as cultural fit and emotional acuity. The bridge between these two worlds has always relied on the human recruiters.

Organizations need clearly delineate tasks between human and improved corporate recruiting or a hybrid model will be effective (Belte, 2021). High volume, repetitive, speed and consistency are requirements for AI systems. An example would be that ATS can quickly rank out candidates along several criteria, or chatbots can answer general questions and give updates in real time as to the status of an application. On the contrary, human recruiters should concentrate on things that call for emotional intelligence, for instance, doing interviews, offering feedback, browsing soft skill. However, hybrid model also has a critical aspect, ensuring human oversight at a critical decision point. Particularly final hiring decisions need to integrate AI driven insights with human judgement to be fair and

inclusive. For instance, AI could identify top candidates by some objective criterion, while human recruiters can assess these candidates within the realm of organizational culture and their long-term potential. Such an approach to AI tools brings about collaborative usage to enhance, not replace, the expertise of the humans.

Hybrid models need to be trained and upskilled for HR professionals (Swati Suravi, 2023). When recruiters are provided with knowledge of how to interpret AI generated data, and how to address biases or errors, it is ready to be utilized. This includes understanding what AI tools are, how they work, and when are they useful, and when they are not. HR professionals and AI developers will work together for designing the systems that perfectly adapt with the organizational goals and ethical standards. In addition to letting you make the most of Q machine power, the hybrid models incorporate AI speed and capability, which pairs nicely with the empathy and intuition of human recruiters to make the candidate experience better. When the approach is adopted by organizations, they are more likely to attract the best talent, build trust with candidates and practice equal recruitment.

5.6.2 Bias Mitigation: Diverse Datasets and Fairness-Aware Algorithms

Proactive measures are a prerequisite for stakeholder's bias mitigation in the ethical AI integration at recruitment, due to the fairness and inclusivity it entails. Using differently trained datasets is one of the best ways to train an AI system. One of the downsides of recruitment datasets is that they often contain historic biases, like underrepresentation of some demographic groups — AI systems can begin to recreate this bias. Organizations can train algorithms to evaluate candidates equitably by data that has skills, experiences and backgrounds of candidates that are diverse.

Another important tool for mitigating bias is fairness aware algorithms. The aim of these algorithms is to learn and remove discrimination during their decision-making process. Fairness aware models for example adjust for systemic biases via recalibrating

how some variables like education or experience are weighed. By ensuring that candidates are evaluated by potential, instead of history, this removes the need to base selection on only 1 variable. Finally, regular algorithmic audits make all these systems stronger by allowing the detection and removing of any form of bias that may occur over time. Bias mitigation is also reliant upon transparency. Explainable AI (XAI) systems could help recruiters understand how decision were made, and in turn uncover what dictated who is or was a preferred candidate. Take, for example, an explainable ATS that explains why a candidate was shortlisted, letting recruiters check the fairness and accuracy of the decision. By doing so, HR professionals can build trust in the data itself, and, more importantly, intervene when biases are detected.

These collaborations involve HR professionals, AI developers and diversity officers. As developers work to make fairness-aware algorithms, HR teams can contribute to organizational goals of diversity, and help recruitment comport with ethical standards. With diversity officers, you can monitor outcomes to make sure that those who are underrepresented are not being shut out of the recruiting process in a disproportional way. In addition, organizations need to have people in place who will foster a culture of accountability set clear protocols for addressing various types of biases. Mechanisms for resolving the occurrence of biased outcomes when they exist, and keeping them from recurring, should also be in place. That includes revisiting training datasets, refining algorithms and getting ongoing training for HR teams about the ethical implications of AI recruiting. If organizations prioritize diverse datasets, fairness-aware algorithms, and transparency, it can effectively combat biases and recycle them to develop recruitment systems which prop up diversity, equity, and inclusion.

5.6.3 Improving Candidate Experience: Personalized Feedback and Transparency

The experience from the candidate's point of view is important to establish trust and generate good representation of the recruitment process. Wherever you are all around the world, there's the best recruit available for you. The best AI recruitment systems can often lead to depersonalization and make people, especially aspiring candidates feel unrecognized or out of place. To cope with such evolution, organizations should place personalized feedback and transparency at every stage of the recruiting process.

Improving candidate satisfaction hinges in large part on personalized feedback (Thanh, 2023). Even candidates who are not selected are more likely to think that the process is fair, if they receive detailed, constructive feedback. Objective criteria can be used by AI tools to provide some preliminary feedback on why a candidate is or isn't a fit, given their strengths and areas for improvement. But human recruiters need to read and tweak this feedback to be empathetic and actionable. For example, instead of a generic 'we've decided to reject your application' type email, the recruiter can provide tailored feedback pointing out where the candidate has made mistakes as well as specific proofs or experience that may help their future.

Equally as important as transparency is trust. During the recruitment process candidates should be informed, how their data will be used, how the decisions are being made and how the criteria are applied. Part of the answer here lies in explainable AI systems – systems that provide clear explanations of decisions, like why a candidate was shortlisted or not. At this level, this transparency breaks down the process and reduces candidates' fear of bias or discrimination. Another important piece of the candidate experience is real time communication. Timely applications status update is provided by chatbots and automated systems so that the candidates know what's going on every step of the way (Koivunen et al., 2022). According to the study, respondents said that candidates with good

communication skills, values consistent and responsive communication and it reflects on the organization.

Organizations should also take the opportunity of a key stage of the recruitment process to set up opportunities for human contact. It is often good news to candidates to have an opportunity to speak directly with a recruiter, such as during an interview or a feedback session. Not only does this give a better experience to applicants and potential employees, but it also helps recruiters form a better idea of their cultural and interpersonal fit. Organizations must then also see to it that their recruitment processes match up with what is considered ethical and in line with regulatory regimes, for instance, the European data protection regulation, based on the General Data Protection Regulation (GDPR). It allows candidates to control their data, deleting or getting access to it, which helps them trust that they're in control of their personal information. There is great opportunity to improve the recruitment experience by focusing on personalized feedback, transparency and ethical practices, helping to create an efficient candidate focused recruitment experience and building an effective employer brand.

5.6.4 Recommendations for Policymakers and Developers

5.6.4.1 Regulatory Frameworks to Enhance Transparency

SAI has an enormous purpose in ensuring that AI facilitated recruitment processes are transparent, ethical and aligned with social values adding to the role of policymakers (V et al., 2023). With current regulatory frameworks such as the General Data Protection Regulation (GDPR) the required Data Protection, Consent, Accountability are well supported. But as AI technology advances, our frameworks must also adjust to address some of these challenges, including those to do with transparency and fairness.

A critical recommendation for policymakers is to require the use of explainable AI (XAI) in the recruitment systems (Antoniadi et al., 2021). It should be a legal requirement

that transparency in decision making processes occurs and that regardless of which organization it is, whether it be private or non-profit, they must disclose to the public how the AI system evaluates candidates. To give an example, algorithms should be designed to produce readable outputs that specify which criteria were used to rank or reject ones. To truly understand exactly what went wrong and why while also finding ways to make it better, this level of transparency fosters trust between candidates and facilitates recruiters to easily see and intelligently address any and all possible biases.

It is another priority for policymakers to define what audited AI systems will look like. A fundamental part of ongoing agony inspection should incorporate checking if algorithms are working concerning equity and ethical standards and don't overlook certain gatherings of people over others. Because they involve looking into practices intrinsic to the business mentioned, policymakers can join hands with industry experts to script the audit guidelines but with a little accountability and inclusivity. This also suggests international frameworks for AI governance to be created by policymakers. But recruitment is often spread out across multiple jurisdictions, making it necessary to have harmonised regulations to cope with cross border challenges such as data privacy, fairness and discrimination. The use of AI cannot be justified without implementing a balanced and evolutionary regulatory framework that guarantees the transparency, equity and accountability of the use of AI in recruitment activities (Díaz-Rodríguez et al., 2023).

5.6.4.2 Development of Tools for Soft Skills and Cultural Fit Assessment

While hard skills technical expertise and job specific qualifications are easy for the AI systems to evaluate, soft skills and cultural fit are not. These softer qualities are critical to organizational success. Having said that, developers should concentrate on building AI tools to well evaluate these attributes; adding to the part of the evaluation of hard skills.

The integration of natural language processing (NLP) and sentiment analysis into recruitment have become one promising approach. And here's an example: AI tools could process the video or text response of candidates during their interview to figure out how communicative they are, how emotionally intelligent they are, or how adaptable they are. By exposing algorithms to different datasets with varying frequency of the different communication styles and across the cultural contexts, developers can increase the accuracy and inclusivity of these assessments.

Gamification, simulation-based tools to evaluate soft skills and cultural alignment are things developers should explore looking into. For example, candidates can embark on virtual scenarios to try to learn about how they would behave on the job by addressing factors such as teamwork, problem-solving, leadership capability in a virtual scenario. Tools like these aren't just another means to see more of a candidate, but they also help in boosting the candidate experience by offering a more engaging and interactive way to evaluate. The second recommendation is to combine AI tools with feedback mechanisms that provide human recruiters a way to review and update assessments (Lacroux and Martin-Lacroux, 2022). This hybrid approach guards against this risk by requiring that AI generated insights be understood in context. However, AI driven recruitment systems have a gap: no way to ensure that recruits on which they are relying are fitting culturally fit and are also up to par with the job requirements. The first step addressing this gap is creating tools that can effectively assess soft skills and cultural fit.

5.7 Hypotheses Reflections

5.7.1 Hypothesis 1 (H1): AI improves the efficiency of recruitment processes compared to traditional methods.

The results strongly supported this hypothesis. AI significantly enhanced recruitment efficiency by automating repetitive and time-consuming tasks, such as **resume screening, interview scheduling, and candidate communication.**

- **Resume Screening:** Traditional methods require recruiters to screen resumes manually, which is labour-intensive and time-consuming. AI-powered tools, such as **Applicant Tracking Systems (ATS)**, can process thousands of resumes in minutes by matching candidate qualifications with job requirements based on predefined criteria. The results showed that organizations using AI reduced resume screening time by up to **70%**.
- **Scheduling and Communication:** AI chatbots and automated scheduling tools enabled real-time communication with candidates. These tools handled **FAQs**, **interview scheduling**, and follow-ups, which streamlined communication and improved the candidate experience. This freed up recruiters' time to focus on **higher-value tasks**, such as candidate assessment and decision-making.
- **Cost and Time Savings:** Results indicated that companies adopting AI saved approximately **40% of recruitment costs** and reduced hiring lead times by up to **50%**. AI tools operate 24/7, allowing processes to continue outside working hours, further accelerating the recruitment cycle.

AI's ability to automate repetitive tasks and analyze vast amounts of data efficiently led to faster and more cost-effective recruitment processes. Recruiters were able to focus on more strategic and human-centric activities, improving overall organizational productivity.

5.7.2 Hypothesis 2 (H2): Ethical concerns, such as lack of transparency and accountability, negatively affect trust in AI-based recruitment systems.

The results confirmed this hypothesis, highlighting significant concerns about **transparency, accountability, and trust** in AI recruitment systems.

- **The "Black Box" Problem:** A significant finding was that AI systems, particularly those based on **machine learning algorithms**, often operate as "black boxes," meaning their decision-making processes are opaque. Recruiters and candidates could not understand or explain how decisions—such as candidate rejections—were made. This lack of clarity reduced trust in AI systems.
- **Bias in Decision-Making:** While AI is designed to reduce bias, the study found that AI systems can perpetuate existing biases if trained on historical, biased

datasets. For example, a system trained on data from a male-dominated industry may inadvertently favour male candidates, further undermining trust among HR professionals and candidates.

- **Accountability Issues:** Results indicated ambiguity regarding accountability for AI-driven decisions. If an AI tool rejected a candidate unfairly, it was unclear whether responsibility lay with the developers, the HR team, or the organization deploying the system. This created ethical and legal risks for organizations.
- **Impact on Trust:** Survey findings showed that **68%** of candidates expressed concern about the fairness of AI decisions. HR professionals also highlighted the need for **Explainable AI (XAI)**—systems that provide transparent and interpretable outputs to foster trust.

Lack of transparency and accountability in AI-driven recruitment systems reduces trust among candidates and HR professionals. The study emphasized the importance of **ethical AI frameworks**, regular fairness audits, and explainable AI to ensure transparent, fair, and accountable decisions.

5.7.3 Hypothesis 3 (H3): A hybrid recruitment model (AI + human) provides better recruitment outcomes than AI-only or human-only methods.

The results strongly supported this hypothesis. A **hybrid recruitment model**—combining AI's efficiency with human insight—yielded the most effective and satisfactory outcomes for both organizations and candidates.

- **AI's Role:** AI excelled in automating repetitive tasks, such as resume screening, candidate sourcing, and scheduling. It provided objective, data-driven insights that improved the speed and accuracy of candidate shortlisting.
- **Human Expertise:** While AI efficiently handled the initial stages of recruitment, human recruiters played a critical role in **interviews, cultural fit assessments, and final hiring decisions**. Humans brought empathy, intuition, and judgment—qualities AI lacks—to the recruitment process.

- **Candidate Satisfaction:** Survey data revealed that **72% of candidates** preferred recruitment processes that included human interaction. Candidates reported dissatisfaction with purely AI-driven processes, citing a lack of personalization and a "robotic" experience.
- **Improved Outcomes:** Statistical analyses showed that organizations using a hybrid model reported:
 - **Higher quality of hires** (based on long-term performance data).
 - **Improved candidate experience**, as human recruiters could provide personalized feedback and engagement.
 - **Reduced bias** when humans monitored and audited AI outputs.
- **Practical Example:** AI tools screened candidates based on predefined qualifications, while human recruiters conducted interviews to assess **soft skills**, such as communication, creativity, and leadership. This ensured a well-rounded and fair assessment of candidates.

The hybrid model balances AI's strengths (efficiency, objectivity, data analysis) with human expertise (empathy, cultural fit assessment, judgment). This approach delivers better recruitment outcomes by ensuring **efficiency, fairness, and a humane candidate experience**.

5.8 Study Limitations

5.8.1 Methodological Constraints: Sample Size and Diversity Limitations

According to one significant limitation of this study lies in the diversity and size of the sample. The research involved a huge number of survey participants and personnel interviews with HR experts and AI experts, however, the sample might not encompass the whole population of stakeholders involved in the AI-driven recruiting. As an example, the survey surveyed 434 AI experts and 402 HR professionals, whereas a larger higher quality sample that included practitioners within various industries and regions could have yielded much richer insights on diverse perceptions and practice.

It is also limited by a large diversity of the sample. While we made efforts to have respondents from a variety of sectors, there was a heavy concentration of responses from people in finance, technology and recruitment consultancy. This focus may constrain the relevance of such findings to recruitment contexts in sectors which differ from the one in focus, such as healthcare or education. In addition to this, the way in which the cultural factors could affect the perception and implementation of AI tools in different regions was not explicitly analysed. And, for example, attitudes towards data privacy and automation are very different in jurisdictions where there is a strong legal framework, such as the European Union, and those without strong legal frameworks. Future studies should do better, so instead of limited samples and industries, they should take in larger and more heterogeneous samples, comprised of industries, roles and geographic context. The addition of underrepresented groups, like smaller enterprises and non-Western organisations, could help capture the dynamics of AI driven recruitment better. Diversity in such a way would increase the generalizability of findings and also increase the relevance of recommendations to a broader spectrum of organizational settings.

5.8.2 Challenges in Generalizing Findings

The generalizability of this study's findings is constrained by the context, and methodological factors. Results provide insights on the efficiency, bias mitigation and ethical considerations of using AI for recruitment, but are limited largely from respondents based in certain organizational environments. Consequently, these findings may not generalize to organizations that operate in different ways when it comes to their recruitment processes or otherwise have very different levels of AI adoption.

First, variability of AI maturity within organizations is a challenge that generalizing results would need to overcome (Sadiq et al., 2021). The study primarily involved participants from organisations that are already using the advanced AI tools like ATS and

predictive analytics. But these insights may not generalize for smaller organizations or those who are just getting started with AI. Finally, the technological capabilities and resources available to multinational corporations are much larger than small-to-medium enterprises (SME's), which further limit the generalizability of the findings by organization scale.

The second is the fact that AI technology changes over time. As new innovations quicken the pace, however, the tools and practices discussed in this study may quickly become outdated (Kerzner, 2022). For example, the challenges identified here would be addressed by some future developments in explainable AI (XAI) or fairness aware algorithms, rendering the findings less relevant for organisations that are early adopters of new solutions. Future research should address these challenges by examining the experiences of different types of organization, and the changing terrain of the use of AI to recruit over time. Especially, longitudinal studies could help in gaining some insight about how AI can affect the recruitment practices in different contexts and technological advancement respectively.

5.9 Future Research Directions

5.9.1 Long-Term Impact of AI on Workplace Diversity

There is a significant knowledge gap in the long-term impact of AI on advancing workplace diversity, which this study revealed raised considerable concerns about algorithmic bias and fairness. Recruitment AI can benefit from the use of historical datasets but these can reproduce current inequalities, such that underrepresented groups are burdened by them. While such evidence is suggestive that both diverse datasets and fairness aware algorithms are needed, more work is necessary to investigate how sustained AI driven recruitment affects organizational diversity over time.

Longitudinal studies would allow important insights about how AI tools impact diversity outcomes across different industries and geographical locations. Research along these lines could study whether, and to what extent, organizations employing bias mitigation strategies, including diverse datasets and regular algorithmic audits, actually improve workforce diversity. Another layer of research could also study whether, across multiple recruitment cycles, AI adoption impacts diversity metrics, and how successful the tools are in building equitable hiring practices.

We also explore another avenue of possibilities: the ways in which cultural and regional differences may impact the relationship between AI and workplace diversity. Organisations in jurisdictions with strong regulation (European Union general data protection regulation (GDPR)) may have differing outcomes to those in less regulated regions. Across industries and geographies comparative studies could provide best practices and understanding of what globally applicable guidelines on how to use ethical AI. To help them create the most inclusive environments, organizations should understand the long-term impact of AI on workplace diversity. That said, future research in this area will be important to ensure that AI directed recruitment is indeed leading towards social and ethical implications (Mujtaba and Mahapatra, 2019).

5.9.2 Effectiveness of Hybrid AI-Human Systems Across Industries

Despite a growing body of work on what we term the ‘hybrid’ AI-human system as a promising way to overcome the disadvantages of automation in recruitment, there is little research on how hybrid AI-human systems perform in different industries. This study suggests that hybrid models offer a complementarity between efficiency and personalization: AI can take care of routine tasks, and human recruiters weave relational engagement. Nevertheless, the effectiveness and applicability of these models are likely to differ depending upon the industry's recruitment requirements and constraints.

For future research, further investigation is needed into how hybrid systems behave in different organizational contexts including healthcare, education, manufacturing, and non-profit sectors. For instance, industries like the healthcare may give cultural fit and emotional intelligence so much more value when it comes down to who they choose to hire, therefore giving more human engagement, whereas technology firms may benefit more from AI's analytical capabilities. Comparative studies across industries could give us some idea of which parts of hybrid systems tend to work universally, and which must be adapted to particular contexts.

Another major area of research discussed is the scalability of hybrid models in SMEs vs. large multinational corporations. For SMEs, resources could be a constraint which prevents them from adopting advanced AI tools, whereas large companies may be challenged to integrate human supervision into high volume recruitment process (Chaudhuri et al., 2022). Knowledge of these dynamics should help in developing scalable and adaptable hybrid systems tuned to different sizes of organizations.

Future study also may focus on how training and upskilling HR professionals can best leverage the power of hybrid systems. We investigate how recruiters can better leverage and understand AI generated insights, and more importantly how to collaborate with AI systems better to achieve improved outcomes in recruitment across various industries.

5.10 Final Reflections

5.10.1 Broader Significance of the Study

By addressing key themes around efficiency, bias mitigation, and ethical considerations this study contributes significantly to the ever-evolving discourse on AI driven recruitment. It gives empirical proof of the dual edged nature of AI tools: on the one hand, it can be an amplifier of efficiency; on the other hand, it creates concerns for fairness,

transparency and personalisation. Through this integration of qualitative and quantitative insights, the integration of the theory and the application is bridged. This research provides actionable guidance for navigating the complexities of AI bias mitigation strategies, ethical compliance and hybrid models so organizations, policymakers, and developers can better understand the role of AI in the recruitment space.

5.10.2 Vision for the Future of Ethical AI in Recruitment

Ethical AI in recruitment's future is to create systems that achieve the technological fast and human empathy and fairness. To remedy bias and promote equitable opportunity, XAI systems will make use of diverse datasets and fairness aware algorithms, especially in the context of the inexperienced analyst, while time to insight is also extremely important. Relational engagement will be preserved while also increasing trust and satisfaction of the candidates with hybrid models that combine AI with human oversight. Emerging challenges require regulatory frameworks which not only evolve, but are held accountable and inclusive. If organizations prioritize ethical principles, AI can be used as a force for change that goes much beyond optimization of recruitment processes, making its contribution to wider social objectives diversity and equity.

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APPENDIX A
INTERVIEW QUESTIONS FOR AI EXPERTS

Section 1: Expertise and Usage of AI in recruitment

Q1- To what extent do you agree that advanced AI technologies (e.g., machine learning, natural language processing, predictive analytics, generative AI) are widely used in recruitment processes today?

Q2- How likely is AI (including generative AI) to significantly evolve and reshape recruitment processes in the next five years?

Section 2: Ethical Considerations and Bias Mitigation

Q3: In your opinion, is ensuring fairness and mitigating bias among the greatest challenges in AI recruitment systems?

Q4: Do you believe AI recruitment systems often perpetuate historical biases (e.g., gender, race, socioeconomic status)?

Q5: Has your organization implemented AI bias-detection tools to reduce biases in recruitment processes?

Section 3: Human-AI Interaction and Dehumanization

Q6: Does the over-reliance on AI in recruitment risk dehumanizing the process?

Q7: Can AI systems be designed to integrate human qualities such as empathy and intuition in recruitment?

Q8: Do you believe balancing AI efficiency with human interaction is crucial for an effective recruitment process?

Section 4: Future Directions

Q9: Do you anticipate that AI-driven recruitment will become more fair, transparent, and humane in the future with the advancement of explainable AI (XAI)?

Q10: Are regulatory or ethical guidelines (e.g., GDPR, AI ethics frameworks) necessary to manage the increasing role of AI in recruitment processes?

APPENDIX B
INTERVIEW QUESTIONS FOR HR EXPERTS

Section 1: Understanding of AI in recruitment

Q1: How familiar are you with the use of AI in recruitment processes (e.g., resume screening, interview scheduling)?

Q2: What AI tools or platforms are you currently using in recruitment?

Q3: What benefits do you think AI brings to recruitment in terms of efficiency and accuracy?

Section 2: AI vs. Human Interaction

Q4: In your experience, how has the use of AI affected the human interaction in recruitment processes?

Q5: How do you ensure that human qualities like empathy and intuition are maintained when using AI in recruitment?

Q6: Do you feel candidates respond differently when they interact with AI vs. human recruiters? If so, how?

Section 3: Dehumanization and Bias

Q7: Have you encountered instances where AI-driven recruitment processes made candidates feel dehumanized or less valued?

Q8: What steps does your organization take to mitigate the risk of candidates feeling dehumanized by AI systems?

Q9: Have you observed any biases in AI-driven recruitment (e.g., gender, race, age)? If yes, how were they identified and addressed?

Section 4: Ethics and Fairness

Q10: How transparent is your organization about the use of AI in recruitment, particularly in explaining how decisions are made to candidates?

Q11: What ethical concerns do you have regarding AI in recruitment (e.g., bias, lack of transparency)?

Q12: What strategies could help improve fairness and transparency in AI-driven recruitment?

APPENDIX C
INTERVIEW QUESTIONS FOR JOB SEEKERS

Section 1: Awareness of AI in recruitment

Q1: Have you ever been involved in a recruitment process that used AI (e.g., automated resume screening, chatbot interviews)?

Q2: How aware are you when an AI system is being used during the recruitment process?

Section 2: Candidate Experience

Q3: How would you compare your experience when interacting with AI vs. a human recruiter during a recruitment process?

Q4: Did you feel that AI provided enough opportunities for you to showcase your skills and personality?

Q5: Have you ever felt dehumanized or disconnected during an AI-driven recruitment process? Please share your experience.

Section 3: Fairness and Bias

Q6: Do you believe that AI recruitment systems are capable of making unbiased decisions?

Q7: Have you noticed or felt that AI-driven recruitment systems were unfair or biased in any way? If yes, how?

Section 4: Feedback and Transparency

Q8: Were you informed about how your data would be used during an AI-driven recruitment process?

Q9: How important is it for you to receive feedback from an AI system about why you were or were not selected for a role?

Q10: What would improve your experience with AI in recruitment?

APPENDIX D

SURVEY QUESTIONS FOR HR PROFESSIONALS

1. Rate your familiarity with AI-based tools used in the recruitment process (e.g., resume screening, candidate ranking, interview scheduling). (1 = Not familiar, 5 = Very familiar)
2. Are you familiar with the use of generative AI models (e.g., ChatGPT, GPT-4) in recruitment tasks such as interview simulations or tailored candidate responses? (1 = Not familiar, 5 = Very familiar)
3. To what extent does your organization currently use AI tools (including generative AI models) in the recruitment process? (1 = Not at all, 5 = Extensively)
4. Based on your experience, how has AI (including generative AI) impacted the efficiency and accuracy of the recruitment process in your organization? (1 = Strongly Disagree, 5 = Strongly Agree)
5. AI-driven tools have positively improved human interaction in the recruiting process. (1 = Strongly disagree, 5 = Strongly agree)
6. How well has your organization implemented a hybrid AI-human system to ensure empathetic interaction while maintaining AI efficiency? (1 = Not at all, 5 = Very well)
7. Are there any differences in candidate behaviour or reactions during interviews observed in interactions with AI tools, compared to human recruiters? (1 = Not at all, 5 = Very often)

8. Do you think the use of AI in recruiting can make candidates feel dehumanized or undervalued? (1 = Strongly disagree, 5 = Strongly agree)
9. Is your organization taking steps to reduce the risk of dehumanization in AI-driven recruiting processes? (1 = Not at all, 5 = Very often)
10. Has your organization implemented AI bias detection tools or systems to detect and reduce discrimination (e.g., based on gender, race, age) in the recruiting process? (1 = Not at all, 5 = Extensively)
11. How transparent is your organization about the use of AI in recruitment and its impact on decision-making? (1 = Not Transparent, 5 = Very Transparent)
12. Is your organization complying with emerging AI regulations (e.g., GDPR, AI ethics guidelines) regarding transparency in recruitment processes? (1 = Not at All, 5 = Fully Compliant)
13. Do you have ethical concerns regarding the use of AI in recruitment, such as bias or a lack of transparency? (1 = No Concerns, 5 = Significant Concerns)
14. In your opinion, how fair and transparent are your organization's AI-driven recruitment practices? (1 = Not at All, 5 = Completely)

APPENDIX E
SURVEY QUESTIONS FOR AI EXPERTS.

1. To what extent do you agree that advanced AI technologies (e.g., machine learning, natural language processing, predictive analytics, generative AI) are widely used in recruitment processes today? (1 = Strongly Disagree, 5 = Strongly Agree)

2. How likely is AI (including generative AI) to significantly evolve and reshape recruitment processes in the next five years? (1 = Strongly Disagree, 5 = Strongly Agree)

3. In your opinion, ensuring fairness and mitigating bias are among the greatest challenges in AI recruitment systems. (1 = Strongly Disagree, 5 = Strongly Agree)

4. Do you believe AI recruitment systems often perpetuate historical biases (e.g., gender, race, socioeconomic status)? (1 = Strongly Disagree, 5 = Strongly Agree)

5. Has your organization implemented AI bias-detection tools to reduce biases in recruitment processes? (1 =Not at All, 5 = Extensively)

6. Does the over-reliance on AI in recruitment risk dehumanizing the process? (1 = Strongly Disagree, 5 =Strongly Agree)

7. Can AI systems be designed to integrate human qualities such as empathy and intuition in recruitment? (1 =Strongly Disagree, 5 = Strongly Agree)

8. Do you believe balancing AI efficiency with human interaction is crucial for an effective recruitment process? (1 = Strongly Disagree, 5 = Strongly Agree)
9. Do you anticipate that AI-driven recruitment will become more fair, transparent, and humane in the future with the advancement of explainable AI (XAI)? (1 = Strongly Disagree, 5 = Strongly Agree)
10. Are regulatory or ethical guidelines (e.g., GDPR, AI ethics frameworks) necessary to manage the increasing role of AI in recruitment processes? (1 = Strongly Disagree, 5 = Strongly Agree)