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The Effectiveness of AI-powered Recruitment Tools in Reducing Hiring Biases: A Data-driven Analysis

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Abstract

Artificial Intelligence has been making its presence increasingly within the recruitment industry and it is expected to be a gamechanger in driving operational efficiency and the incremental removal of bias. And yet, as these tools become more widespread, one key question remains: can an algorithm really rise above the biases baked into its data and design? The paper contributes to the emerging literature on field studies of AI-enabled recruitment by examining how human resource professionals, and recruiters draw from their practices and experiences to make sense of AI's operation in real contexts. Through qualitative research, the study collected data via semi-structured interviews that generate in-depth understanding of AI operations within different hiring scripts. The results paint a simultaneous picture. One side is that AI speeds up the process of evaluating candidates and adds an element of procedural regularity to offset some kinds of human subjectivity. Conversely the evidence reveals continuing blind spots where skewed data sources and algorithmic limitations continue to discriminate against non-standard candidates, as well as ignore nuances such as cultural fit and soft skills. Moreover, the debate has also brought out existential ethical worries about transparency, accountability and the black box character of automatic decision-making. The findings highlight the fact that AI cannot be used as a stand-alone solution; rather, its ethical application depends on strict human oversight and a dedication to open standards. This study offers human resource leaders a strategic framework by bridging the gap between the theoretical promise of AI and its practical challenges. It claims that a purposeful blend of algorithmic speed and human ethical judgment is the only way to create a more equitable and inclusive workforce.

Keywords: *AI-Powered Recruitment; Bias Reduction; Hiring Practices; Human-AI Collaboration; Talent Acquisition.*

1. Introduction

Organizations are under increasing pressure to create inclusive, diverse workplaces in addition to attracting top talent in the fiercely competitive global job market. However, traditional hiring procedures are still prone to unintentional biases like stereotyping and affinity bias, which may affect judgment and restrict diversity. AI-powered recruitment tools have the potential to reduce subjectivity and increase efficiency in screening, candidate matching, and predictive analyses by automating routine hiring tasks and supporting data-driven decisions.

The adoption of these technologies is still in its infancy in Sri Lanka. Leading companies like Virtusa, MAS Holdings, and Dialog Axiata have started incorporating AI to improve hiring efficiency, but many organizations face challenges like inadequate AI infrastructure, data privacy issues, and human resource (HR) professionals' resistance to change. The true effects of AI on hiring equity and diversity are still unknown locally due to these difficulties and the nation's developing AI ecosystem. However, AI has the potential to change recruitment in Sri Lanka toward more inclusive and effective practices if it is applied with good training, moral standards, and encouraging regulations.

There is conflicting evidence regarding AI's capacity to lessen hiring biases, despite its increasing use in recruitment worldwide. While some studies emphasize improvements in objectivity, others caution that discrimination may be sustained or even made worse by algorithmic bias. Furthermore, there is an absence of empirical data from emerging markets, especially Sri Lanka. In order to address a significant knowledge gap, this study examines how well AI-powered recruitment tools lessen hiring bias in Sri Lankan organizations. To address this gap, the study has three primary objectives:

1. Determine whether and how much hiring bias is reduced by AI-powered recruitment tools.
2. Compare AI-driven recruitment with traditional hiring methods in fairness, efficiency and workforce diversity.
3. Analyze HR professionals’ opinion and ethical concerns regarding the use of AI-powered recruitment and make useful suggestions for its equitable application.

Aligned with these objectives, the study answers three central research questions:

1. Does the use of AI in recruitment reduce hiring bias, and under what conditions?
2. How do AI-based and traditional hiring methods differ in fairness, efficiency and diversity outcomes?
3. What perceptions, ethical issues and best-practice considerations do HR professionals identify for optimizing AI-based recruitment?

Very little is known about how these tools work in developing markets like Sri Lanka, despite the fact that research from around the world shows both the potential and limitations of AI in reducing hiring biases. Findings from Western contexts cannot be assumed to apply locally due to differences in data infrastructure, cultural hiring norms, linguistic diversity and technological readiness. There is an obvious research gap due to the lack of localized empirical evidence. In order to close the gap, this study assesses how well AI powered hiring tools mitigate bias in Sri Lankan workplaces. In addition to providing evidence for larger discussion on the moral application of AI in hiring, the findings are intended to assist Sri Lankan organizations in enhancing hiring procedures while promoting diversity and inclusion.

2. Literature Review

2.1 Evolution and promise of AI in recruitment

Research shows the recruitment process has evolved from manual practices to digital systems and, most recently, to AI-driven ecosystems that can influence candidate evaluation and selection. Scholars describe this shift as moving from Recruitment 1.0, through Recruitment 2.0 with digital boards and ATS, to Recruitment 3.0 where algorithms play a central role in screening, matching, and predictive analyses (Mujtaba & Mahapatra, 2024). This transition promises faster, more data-driven decisions: AI chatbots, resume screening tools, video interviewing platforms, and predictive analytics streamline tasks that once consumed substantial HR time (D'Souza, & Paiithannkar, 2022). Empirical work highlights clear gains in efficiency. For example, studies report substantial reductions in screening time and administrative burden when AI tools are deployed, alongside improved candidate matching accuracy compared to traditional keyword methods (Basha, et al., 2024). These findings align with wider perspective that automation can accelerate hiring cycles and free HR staff to focus on higher-value activities. Yet even proponents warn that such efficiency does not automatically guarantee fair or ethical outcomes without careful design and oversight.

2.2 Efficiency gains versus potential depersonalization

While AI's efficiency benefits are well documented, some evidence cautions against over-reliance. Studies on automated candidate engagement note dramatic decreases in HR workload and improvements in candidate satisfaction, sometimes by as much as 30-80 percent in reported metrics (Basha, et al., 2024). However, critics argue that extensive automation can depersonalize the candidate experience, especially in cultures or roles that value relational interaction (Albassam, 2023). Similarly, predictive analytics can forecast candidate success, acceptance rates, or turnover patterns using machine learning, theoretically supporting better talent decisions Schleder, et al., 2019. Yet even optimistic accounts admit that algorithms struggle with subjective, context-dependent factors like cultural fit or team dynamics, areas where human judgment remains vital (Albassam, 2023; Chen, 2023). This tension suggests that the value of AI lies less in full replacement of human judgment and more in complementary use, boosting speed and consistency while still relying on human interpretation for nuanced decisions.

2.3 Bias reduction claims and contrasting evidence

A major debate centers on AI's ability to mitigate hiring bias. Supporters claim AI can standardize evaluations and focus strictly on qualifications, thereby reducing the influence of human biases related to gender, ethnicity, or age (Mackereth & Drage , 2022). Some empirical studies report measurable reductions in bias complaints or disparities when AI is applied to resume screening or early stages of selection (Basha, et al., 2024). However, a strong counter-argument warns that AI systems can inherit and perpetuate historical biases embedded in training data. Mackereth & Drage , 2022 and others highlight examples where AI favors candidates who resemble historically successful employees, inadvertently reinforcing existing inequalities. Further research notes that even subtle aspects such as language patterns or word choices in resumes can introduce discrimination if models are not carefully monitored (Oman, Siddiqua, & Noorain, 2024). These contrasting findings underscore that AI is neither a guaranteed solution nor an automatic problem; its impact depends on data quality, model design, and continuous oversight. The literature thus oscillates between cautious optimism and critical scrutiny, rather than presenting a unified view.

2.4 Ethical, practical, and operational challenges

Beyond bias, scholars raise broader ethical and operational issues. The opacity of many AI models creates transparency concerns, limiting both candidate and recruiter understanding of how decisions are made (Rathnayake & Gunawardana, 2023). The study by (Balasubramaniam, Kauppinen, Rannisto, Hiekkanen, & Kujala, 2023) argues that interpretability is essential for fairness and accountability. Privacy and consent challenges emerge when AI collects extensive candidate data, sometimes using sensitive indicators, mandating compliance with data protection laws and robust security measures (Chen, 2023; Rathnayake & Gunawardana, 2023). Operational barriers also loom. Integrating AI tools with legacy HR systems, overcoming skepticism among recruiters, and handling technical constraints are documented hurdles, especially in organizations with limited infrastructure (Albassam, 2023). Cases of over-dependence on AI raising concerns about missing soft skills or contextual insights reflect a consistent theme: practical realities and cultural norms shape how AI performs in real work settings, and technology alone cannot solve all human resource problems (Stuss & Fularski, 2024; Mujtaba & Mahapatra, 2024).

2.5 Contexualizing AI in Recruitment for Sri Lanka

While the global studies on AI in recruitment is largely dominated by Western narratives, where robust digital infrastructures and mature legal frameworks facilitate seamless adoption, the Sri Lankan context offers a far more complex reality. Implementing AI in a local setting is not a simple plug-and-play endeavor; rather, it requires navigating a unique intersection of linguistic diversity, evolving labor regulations, and deeply ingrained cultural norms that standard algorithms are often ill-equipped to interpret.

In Sri Lanka, the hiring ecosystem is historically characterized by what many call a relational culture. Traditional recruitment often centers on personal networks, informal referrals, and the subtle nuances of social trust. These deeply rooted human interactions represent a domain where AI frequently weakens, as a machine lacks the cultural intelligence to replicate the subjective, yet vital, judgment used in relationship-based hiring. Furthermore, there is the challenge of algorithmic translation, can a tool designed for a Western corporate environment truly understand the professional ethos and local linguistic subtleties of the Sri Lankan workforce?

Consequently, while AI holds the undeniable potential to dismantle overt prejudices and streamline the administrative burden of hiring, its efficacy remains a subject of debate. The transition from traditional, network-led recruitment to data-driven automation is a sensitive one. There is a strong need for more localized, empirical research to determine how these tools can be integrated without eroding the human-centric values that define the Sri Lankan workplace. Ultimately, the goal is not merely to adopt AI, but to adapt it in a way that respects the local context while striving for greater organizational equity.

2.6 The need for hybrid human-AI approaches

A balanced, hybrid approach that combines AI's speed and pattern recognition with human judgment, ethical oversight, and ongoing auditing is a common recommendation across various studies (Mujtaba & Mahapatra, 2024; Johnson, L., Smith, K, & Brown, T, 2020). These methods acknowledge that AI can improve fairness by using consistent criteria, but only if it is trained on representative data, routinely audited, and augmented by human review to address what models are unable to capture. This synthesis of viewpoints offers a practical solution that emphasizes transparency, fairness-aware algorithm design, and human responsibility while using AI as decision support rather than as an independent decision maker.

3. Methodology

3.1 Research Design

In order to investigate how AI-powered recruitment tools affect hiring biases in Sri Lankan organizations, this study used a qualitative research design. Because it allows for a thorough understanding of HR professionals' experiences, perceptions, and interpretations of AI-driven hiring practices that cannot be sufficiently captured by quantitative surveys alone, a qualitative approach was chosen.

The primary data were collected through semi-structured interviews and phone interviews with HR Professionals who actively use AI powered recruitment tools. The primary insights were supported by the secondary data from industry reports and scholarly literature.

3.2 Participants and Sampling Strategy

The study included thirty HR professionals from various industries such as IT, Manufacturing, Telecommunications, Apparel and services. The study used purposive sampling to identify people who were directly exposed to AI powered recruitment tools, to make them valuable sources of information for the study's goals.

Due to the comparatively low uptake of AI tools in Sri Lanka, this sampling strategy was appropriate. The sample size is in line with the standards of qualitative methodology, which state that twenty to thirty participants are frequently adequate to detect thematic patterns. Data saturation was reached when no new themes emerged during the final interviews, indicating adequacy of the sample.

3.3 Data Collection Procedure

Semi-structured interviews and phone calls with HR specialists were used to gather primary data. Perceptions of AI tools, experiences with bias detection, operational difficulties, and ethical concerns are just a few of the topics covered in the interview guide that was created, (see Appendix). Depending on participant availability, interviews lasted from fifteen to twenty minutes. Few interviews were audio recorded with permission and then transcribed for analysis. Most of the situations, thorough written notes were made. The theoretical framework and findings interpretation were supported by secondary data, such as journal articles, industry reports, and practitioner publications.

3.4 Data Analysis

Thematic analysis was used to examine the data in accordance with six-step framework: the first step was Familiarization which is the process of reading and re-reading interview notes and transcripts. The second step was Initial Coding which is the process of manually coding significant passages about bias mitigation, tool efficacy, transparency issues, and implementation difficulties. Third step was identification of themes which is the process of organizing codes into more general patterns. In this research themes such as perceived improvements in decision-making consistency, practical adoption barriers, algorithmic fairness issues, and limitations in soft-skill evaluation were identified as main themes. The next step was examining themes where themes may be improved, combined, or eliminated to guarantee internal coherence. The fifth step was defining and naming themes which is the process of creating precise definitions for the final themes and the last step was interpreting the results by combining literature and thematic insights. Since the dataset was manageable, coding was done manually without the use of specialized qualitative software.

3.5 Ethical Considerations

Prior to interviews and data collection, informed consent was obtained from each participant after they were made aware of the study's objectives. Prior to starting interviews, verbal consent was acquired. Recordings were safely stored, and all data was anonymized to protect participant identities.

4. Results

In accordance with the format of the research questions, the study's results are presented thematically. Inductive coding of interview transcripts and phone conversations with thirty HR professionals from various industries led to the development of themes. The themes are based on the participants' actual experiences using AI-powered hiring tools in Sri Lanka.

4.1 Overview of Participants

Participants included recruitment managers, technical recruiters, and HR executives from a variety of fields, including IT, manufacturing, apparel, education, and HR services. Their experience ranged from less than a year to more than ten years, which gave them a wide range of opinions on hiring with AI help. The different positions and sectors represented give a deep understanding of how AI is accepted, seen, and challenged in different organizational settings. The below table shows the summary of positions held by participants and the industry they belong to, their experience and the AI Recruitment tools used by them.

4.2 Theme 1: Adoption and Use of AI-Powered Recruitment Tools (RQ1)

Table 1: Distribution of Participants by Industry and Experience

Industry	HR Roles	Primary AI Tools Used	Experience (Years)
Apparel	Screening, Recruitment Manager	HireVue, Workday	Less than one, Seven to ten
IT	Technical Recruitment Partner	LinkedIn Talent Insights, Talendary	One to three, more than ten
Manufacturing	Overlook Recruitment Team	LinkedIn Talent Insights, SAP	More than ten
Education & Training	Head Teacher, Shortlisting	LinkedIn Talent Insights	Four to six, One to three
Human Resources & Recruitment	Interviewer, Recruitment Executive	SAP SuccessFactors	More than ten, four to six

Participants of this study reported using a variety of AI tools such as LinkedIn Talent Insights, SAP SuccessFactors, and Workday Recruiting being the most common. A smaller percentage, particularly in larger companies with sophisticated digital infrastructure, relied on customized tools. The main applications of AI tools were initial filtering, profile matching, candidate shortlisting, and resume screening. According to an IT recruiter:

"LinkedIn Talent Insights helps us map profiles quickly. It reduces our workload significantly compared to manual sourcing."

However, adoption of these tools differed by sector. Most commonly, IT companies showed greater usage and deeper integration, whereas participants in the manufacturing and apparel industries reported more traditional adoption patterns. This theme shows that while AI-supported recruitment is growing, its use is still uneven across industries due to differences in organizational readiness and technological capability.

4.3 Theme 2: Perceived Effectiveness of AI Tools in Improving Efficiency

Table 2: AI Recruitment Tool Comparison

Tool	Advantages	Challenges	Bias Mitigation Effectiveness
LinkedIn Talent Insights	"Data-driven matching" "Wide talent pool"	"Overlooks contextual nuances"	"Reduces cultural fit bias"
SAP Success Factors	"Processes 500+ resumes/hour"	"Opaque decision-making"	"May reinforce keyword bias"
Custom Tools	"Tailored algorithms minimize bias"	"High development costs"	"Highest satisfaction"

Table 2 shows how participants of this study perceive the different AI recruitment tools in terms of advantages, disadvantages and their effectiveness in bias mitigation. Most of the participants agreed that AI tools facilitated data-driven decision-making, decreased administrative work, and shortened recruitment cycles. One HR manager from manufacturing noted:

"In a matter of minutes, AI evaluates hundreds of applications. It eliminates the need for manual labour for days".

Similarly, interviewees reported increased objectivity and consistency, claiming that AI lessens individual preferences in early screening. However, participants also noted functional limitations. Several participants pointed out, AI "*overlooks contextual information*" and "*misses nuances that a human recruiter can catch*". Others pointed out that tools occasionally give priority to "surface-level indicators such as keywords," which has an impact on the ranking of candidates. Therefore, participants stressed the need for human oversight to interpret context and evaluate candidate suitability beyond technical qualifications, even though AI improves efficiency.

4.4 Theme 3: Effectiveness of AI in Reducing Hiring Biases (RQ2)

Participants generally agreed that AI contributed to reducing common human biases such as gender favoritism, nepotism, and affinity bias. One HR executive shared:

"AI doesn't care about gender or background. It filters based on requirements, which helps us stay objective."

However, participants also stressed that bias reduction was not guaranteed. They noted that the effectiveness of these AI recruitment tools in reducing biases depended on training data, algorithm transparency, and how the tools were implemented.

A senior recruiter explained the challenge: *"If the data fed into the system is biased, AI will simply repeat the same patterns."* In this case, custom-made tools were thought to be better because companies could change the training datasets and screening criteria. This theme shows that the people who took part in the study have a deep understanding that AI can help with some biases but may also make or strengthen others without meaning to.

4.5 Theme 4: Risks and Challenges of Using AI Recruitment Tools (RQ3)

Participants identified several risks which were grouped into technical, operational, and cultural challenges. Technical Challenges include Algorithmic opacity, Difficulty interpreting automated decisions, Issues with screening non-standard resumes and Dependence on keyword-based filtering. One participant said:

> *"Some strong candidates get rejected because their wording doesn't match what the AI expects."*

When it comes to the cultural and organizational resistance, several HR professionals expressed reluctance toward full automation: *"We still depend heavily on face-to-face interviews. AI cannot capture attitude or personality."* Another challenge is limited soft-skill assessment. Many HR professionals stressed that AI tools struggle with evaluating cultural fit, emotional intelligence and interpersonal attributes. These limitations reinforced that AI cannot replace human judgment in final decision-making, especially for roles requiring high interpersonal skills.

4.6 Theme 5: Ethical Concerns in AI-Assisted Recruitment

Ethical considerations emerged as a central pillar of the participants' discourse, revealing a deep-seated concern for the systemic implications of automated hiring. Foremost among these issues was the persistent challenge of algorithmic bias. Rather than viewing AI as a neutral arbiter, several participants identified recurring patterns where the software mirrored existing societal prejudices. One respondent illustrated this by noting, "*Our tool initially favored candidates from certain universities. We had to adjust the settings after noticing the trend*." This suggests that without constant human intervention and calibration, AI tools risk automating and scaling historical inequality under the guise of technical objectivity.

Participants expressed significant professional discomfort when navigating opaque decision-making processes that they could not fully deconstruct. This lack of "explainability" creates a functional gap in accountability; as one participant remarked, "*The tool rejects candidates but doesn't explain why. It's difficult to justify decisions to applicants*." This sentiment emphasizes a conflict between the tools' effectiveness and the moral duty to give candidates insightful feedback.

Lastly, the discussion covered the increasingly sensitive topic of informed consent and data privacy. Participants expressed concerns about the security of applicant data and the jurisdiction of privacy regulations as recruitment tools become increasingly integrated into global digital platforms. Strong data policies and rigorous adherence to international compliance standards were emphasized collectively. In the end, these results imply that although AI offers unquestionable speed, it also adds a layer of ethical complexity that necessitates a "human-in-the-loop" strategy to guarantee that final hiring decisions remain morally and legally sound.

4.7 Theme 6: Human-AI Collaboration in Recruitment Decision-Making

Across interviews, there was strong consensus that the most effective hiring approach combines AI-driven screening with human evaluation. Participants consistently described AI as a "supporting tool," not a replacement: *"AI helps with the heavy lifting, but humans must make the final call."*

Table 3: Comparison of AI-Driven and Human-Driven Recruitment

Criteria	AI-Driven	Human-Driven
Skills	"Keywords, certifications"	"Hidden talents"
Cultural Fit	"Limited assessment"	"Intuitive judgment"
Bias	"Standardized but may inherit biases"	"Unconscious biases"

While humans were valued for their soft skills, cultural fit, and ethical reasoning, AI was valued for its speed, consistency, and objective filtering. Table 3 shows that while AI is excellent at processing structured data, such as certifications, it is not as good at evaluating interpersonal dynamics and hidden talents, which are areas where human recruiters show intuitive judgment.

Even though AI can standardize screening, number of participants pointed out that if algorithmic tools are trained on faulty historical data, they may introduce new biases. On the other hand, human recruiters can adjust their judgment to contextual and ethical nuances, despite being prone to unconscious biases. This emphasizes the need for hybrid hiring models, especially in cultural settings like Sri Lanka where relational factors have a significant impact on hiring decisions.

4.8 Theme 7: Recommendations from Participants

Beyond identifying challenges, the study participants provided a strategic roadmap for the future of AI-integrated hiring. These recommendations were not merely technical adjustments; rather, they represented a call for a paradigm shift toward Responsible AI which is an approach that balances computational efficiency with social equity. The primary consensus among respondents centered on the need to move away from a set-and-forget mentality, advocating instead for a model defined by continuous attentiveness and localized adaptation.

Diversifying training datasets is a crucial first step, according to multiple practitioners. Participants argued that the AI will unavoidably reproduce past exclusions if the underlying data lacks demographic diversity. In order to address this, they suggested a double-track strategy that included rigorous, frequent audits of screening results after preventative data selection. As an essential "sanity check," these audits would guarantee that the algorithm's reasoning stays consistent with the company's real diversity objectives over time.

The participants also stressed the need for radical transparency to replace the "black box" aspect of AI. They proposed that maintaining institutional trust requires giving recruiters and candidates understandable justifications for automated decisions. This transparency is closely linked to the principle of human-in-the-loop oversight. There was a strong sentiment that while AI is an excellent tool for processing vast quantities of data, it should never be the final arbiter of talent. Human intuition and ethical judgment are particularly vital in the final stages of the hiring process to interpret the nuances that an algorithm might miss.

Finally, a unique and significant finding was the demand for contextual localization. The "one-size-fits-all" strategy of global AI models, which are frequently trained on Western corporate standards, was cautioned against by the participants. Rather, they suggested tailoring AI tools to the unique linguistic and socioeconomic context of Sri Lanka. Organizations can guarantee that implementation of AI is not only successful but also culturally relevant and morally sound by firmly establishing these global technologies in local realities. When combined, these observations provide a useful framework for any company looking to modernize hiring practices while preserving human dignity.

5. Discussion

The effectiveness of AI-powered recruitment tools in decreasing hiring biases and increasing hiring process efficiency was investigated in this study. According to the findings, which are in line with earlier studies (D'Souza, & Paiithannkar, 2022; Basha, et al., 2024), AI may speed up hiring, improve the candidate experience, and reduce some types of bias. These results, which highlight how technology can assist decision-making while still requiring human judgment, are consistent with the human-technology interaction framework. In line with international research findings, the study did, however, also highlight issues with algorithmic bias, ethical ramifications, and an excessive dependence on AI (Dastin, 2018; Basha, et al., 2024).

5.1 Benefits of AI-Powered Recruitment Tools

The consensus among study participants suggests that AI is no longer just an outlying tool but a primary driver of operational efficiency. By automating the more mechanical aspects of recruitment, such as the initial screening of resumes and the logistical hurdle of scheduling, AI frees up human capital for higher-value engagement. This shift aligns closely with the observations of (Basha, et al., 2024) and (Parasa, 2024), who argue that the reduction in time-to-hire directly correlates with more precise candidate-job alignment. Beyond mere speed, the integration of AI-driven chatbots and virtual assistants ensures a 24/7 engagement cycle, which (Zimmermann, A, Schmidt, R, & Müller, S, 2016) identify as a key factor in strengthening employer branding in a competitive talent market.

From a theoretical standpoint, these findings give weight to socio-technical systems theory. This framework suggests that organizational success isn't just about the technology itself, but the synergistic relationship between human intuition and algorithmic power.

Perhaps the most compelling argument made by participants is the capacity for AI to act as a neutralizer for human subjectivity. According to Mehrotra & Khanna, 2022; Basha, et al., 2024, when AI-based systems are properly designed, they can theoretically avoid the unconscious biases present in traditional interviewing by using objective criteria. But this isn't a fix. The people who participated were quick to note that human oversight continues to be the process's ethical foundation, which is consistent with the larger body of literature on algorithmic fairness. Without it, the AI could be misled by limitations in historical data. However, when used strategically, this data-driven approach enables predictive hiring, giving HR departments the ability to predict long-term success and turnover with a level of insight that was previously unattainable (Parasa, 2024).

5.2 Challenges and Ethical Concerns

The shift to AI-driven hiring is fraught with ethical dilemma despite the optimism surrounding its advantages. The results of this study on algorithmic bias serve as a sobering reminder of the mirror effect, which occurs when AI models unintentionally reproduce historical discriminatory patterns (Dastin, 2018; Basha, et al., 2024). From targeted job advertisements to the subtleties of video interview analysis, these biases are not limited to a single stage (Oman, Siddiqua, & Noorain, 2024; Suen & Hung, 2023). This highlights an important theoretical fact: AI systems inherit the sociocultural prejudices of the companies that create them; they do not exist in a vacuum.

A prime example often cited in this discourse is the Amazon case, where an AI tool was found to be actively penalizing female applicants because it was trained on a decade of male-dominated resumes (Dastin, 2018). Such instances highlight why transparency and accountability are now the focal points of the HR tech debate. Participants echoed the concerns found in the work of (Beri, A.P Rao, Gawali, Raj, & Jadhav, 2023) regarding the explainability of AI, essentially, if a machine makes a life-changing decision for a candidate, HR must be able to explain how and why.

Ultimately, the effectiveness of AI is tethered to the quality of the data it consumes. As (Albassam, 2023) notes, data dependency remains a significant vulnerability. To mitigate this, the study's participants strongly advocated for hybrid human-AI systems. This middle-path approach, rooted in the principles of responsible HR, ensures that technology handles the data while humans provide the ethical and contextual guardrails necessary for a fair hiring ecosystem.

5.3 Mitigation Strategies for Bias and Ethical Issues

In line with pre-processing, in-processing, and post-processing techniques in earlier research, participants recommended fairness-aware algorithms and frequent audits to address AI bias and ethical concerns (Mujtaba & Mahapatra, 2024). These methods include pre-processing, which involves removing biased training data, in-processing, which involves incorporating fairness constraints into algorithms, and post-processing, which involves checking results for demographic differences to guarantee equity throughout the hiring process. Human-AI collaboration was emphasized in accordance with the socio-technical perspective that human judgment and AI outputs must be integrated to achieve optimal results (Akinnagbe, 2024).

Organizations in Sri Lanka may consult international frameworks like the GDPR for data privacy guidelines in the absence of local AI governance, but contextual adaptation is still necessary for culturally relevant implementation. HR professionals in Sri Lanka rely on self-regulation due to the lack of legally binding AI governance, which is similar to issues in other emerging markets. This supports earlier research showing that local organizational culture, legal frameworks, and data governance procedures all affect how well AI is implemented (Parasa, 2024).

5.4 Limitations

Despite the fact that the study offers valuable qualitative insights, a number of limitations should be noted. First, thirty HR professionals made up the sample, which is suitable for qualitative research but may restrict the findings' applicability to all Sri Lankan industries. Second, semi-structured interviews and telephone conversations were used to gather data. These methods rely on self-reported perceptions and may involve selective recall or personal biases. Third, access to participants with a great deal of practical experience was restricted because AI recruitment tools were not widely used in Sri Lanka. These limitations highlight opportunities for future research to use larger samples, mixed-method designs, and longitudinal approaches to validate and expand upon the present findings.

6. Conclusion

This study examined how well AI-powered recruitment tools reduce hiring biases using qualitative data from HR professionals across Sri Lankan industries. The findings demonstrate how AI boosts productivity through automation and lessens biases like gender and affinity bias through standardized screening. The study also demonstrates that algorithmic biases, difficulties in evaluating soft skills, and moral concerns like accountability and transparency necessitate ongoing human oversight. These results demonstrate that hybrid human-AI decision-making remains essential despite the widespread use of AI, particularly in developing countries like Sri Lanka where legal and technical frameworks are still being established (Dastin, 2018; Basha et al., 2024). By highlighting the connection between algorithmic efficiency and human judgment, this study contributes to the theoretical conversation on AI in HR.

7. Practical Implications

This study recommends that businesses using AI in recruitment use hybrid human-AI models, where humans make the final hiring decisions and AI handles initial screening. Regular bias audits of training data and algorithmic outputs are necessary to find and fix disparities. Transparency measures, like providing candidates with succinct explanations for AI-driven decisions, are also essential to maintaining fairness and confidence in the hiring process.

8. Limitations and Future Research

The study's limitations include Sri Lanka's early adoption of AI, a small sample size, and the use of self-reported data. These restrictions caution against drawing too many conclusions from the findings. Future research should fill in the gaps by examining the following areas: (a) regional adaptations of AI tools in different emerging markets; (b) long-term effects of AI on workforce diversity and retention; (c) HR training programs to improve recruiters' AI literacy; and (d) industry-specific efficacy of AI recruitment in technical versus non-technical sectors. "*AI is a tool, not a replacement*," as one participant noted, emphasizing the need for balanced human-AI collaboration for the moral and effective use of AI.

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References

Akinnagbe, O. B. (2024, November). Human–AI collaboration: Enhancing productivity and decision-making. *International Journal of Education Management and Technology*, 2(3), 387-417. https://doi.org/10.58578/ijemt.v2i3.4209

Albassam, W. A. (2023). The power of artificial intelligence in recruitment: An analytical review. *International Journal of Professional Business Review*, 8, 1-25. https://doi.org/10.26668/businessreview/2023.v8i6.2089

Balasubramaniam, N., Kauppinen, M., Rannisto, A., Hiekkanen, K., & Kujala, S. (2023, July). Transparency and explainability of AI systems: From ethical guidelines to requirements. *Information and Software Technology*, 159. https://doi.org/10.1016/j.infsof.2023.107197

Basha, D., Rajitha, M., Roslin, A. M., Thoti, D., Khalid R. P., M., & Mishra, D. (2024). AI-powered recruitment and employee selection: Evaluating bias and fairness. *The Journal of Computational Science and Engineering,* 14(1). https://doi.org/10.52783/eel.v14i1.1107

Beri, S., Rao, A. P., Gawali, C., Raj, V., & Jadhav, D. (2023, August). AI-powered hiring: An analysis of advantages and pitfalls. I*nternational Journal of Engineering, Science, Technology and Innovation (IJESTI),* 3(8). https://doi.org/10.31426/ijesti.2023.3.8.3613

Black, J. S., & van Esch, P. (2020). AI-enabled recruiting: What is it, and how should a manager use it? *Business Horizons,* 63(2), 215–226. https://doi.org/10.1016/j.bushor.2019.12.001

Chen, Z. (2023). Ethics and discrimination in artificial intelligence-enabled recruitment practices. *Humanities and social sciences communications*, *10*(1), 1-12. https://doi.org/10.1057/s41599-023-02079-x

Dastin, J. (2022). Amazon scraps secret AI recruiting tool that showed bias against women. In *Ethics of data and analytics* (pp. 296-299). Auerbach Publications.

D'Souza, M., & Paiithannkar, D. (2022). AI-powered recruitment: Transforming the hiring process. *IJEETE Journal of Research*, 9(2), 181-184.

Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough? An experiment with data saturation and variability. *Field Methods*, 18(1). https://doi.org/10.1177/1525822X05279903

Huff, L. J., & Sutherland, L. F. (2021). Automated video-interview personality assessments: Reliability, validity, and generalizability investigations. *Journal of Applied Psychology,* 107(8), 1323-1351. https://doi.org/10.1037/apl0000695

Johnson, L., Smith, K., & Brown, T. (2020). AI in recruitment: Transforming the hospitality and tourism industry. *Journal of HR Technology,* 12(3), 45-60. https://doi.org/10.55938/ijgasr.v2i2.50

Mackereth, K., & Drage, E. (2022, October). Does AI debias recruitment? Race, gender, and AI's "eradication of difference." *Journal of Organizational Behavior,* 10(3), 67-80. https://doi.org/10.1007/s13347-022-00543-1

Mehrotra, S., & Khanna, A. (2022). Recruitment through AI in selected Indian companies. *Metamorphosis,* 21(2), 31–39. https://doi.org/10.1177/09726225211066220

Min, A. (2023, October). Artificial intelligence and bias: Challenges, implications, and remedies. *Journal of Social Research,* 2(11), 3808-3817. https://doi.org/10.55324/josr.v2i11.1477

Mujtaba, D. F., & Mahapatra, N. R. (2024). Fairness in AI-driven recruitment: Challenges, metrics, methods, and future directions. *arXiv preprint arXiv:2405.19699*.

Oman, Z., Siddiqua, A., & Noorain, R. (2024). Artificial intelligence and its ability to reduce recruitment bias. *World Journal of Advanced Research and Reviews*, 24(1), 551-564. https://doi.org/10.30574/wjarr.2024.24.1.3054

Parasa, S. (2024). Impact of AI in recruitment and talent acquisition. *Human Resource and Leadership Journal,* 9(3), 78-83. https://doi.org/10.47941/hrlj.2117

Rathnayake, C., & Gunawardana, A. (2023, November). The role of generative AI in enhancing human resource management recruitment, training, and performance evaluation perspectives. *International Journal of Social Analytics,* 8(11), 13–22. https://norislab.com/index.php/ijsa/article/view/53

Rathore, S. (2023). The impact of AI on recruitment and selection processes: Analysing the role of AI in automating and enhancing recruitment and selection procedures. *International Journal for Global Academic & Scientific Research,* 2(2), 78-93. https://doi.org/10.55938/ijgasr.v2i2.50

Schleder, G., Padilha, A., Acosta, C., & Costa, M. (2019, May). From DFT to machine learning: Recent approaches to materials science - A review. *Journal of Physics: Materials,* 2(3). https://doi.org/10.1088/2515-7639/ab084b

Stuss, M., & Fularski, A. (2024, January–March). Ethical considerations of using artificial intelligence (AI) in recruitment processes. *Education of Economists and Managers,* 71(1), 53-67. https://doi.org/10.33119/EEIM.2024.71.4

Sutherland, L. F., & Huff, L. J. (2020). Intelligent video-interview agent used to predict communication skill and perceived personality traits. *Human-centric Computing and Information Sciences,* 10(1). https://doi.org/10.1186/s13673-020-0208-3

Suen, H.-Y., & Hung, K.-E. (2023, June). Building trust in automatic video interviews using various AI interfaces: Tangibility, immediacy, and transparency. *Computers in Human Behavior*. https://doi.org/10.1016/j.chb.2023.107713

Xue, L., & Pang, Z. (2022, June). Ethical governance of artificial intelligence: An integrated analytical framework. *Journal of Digital Economy,* 1(1), 44–52. https://doi.org/10.1016/j.jdec.2022.08.003

Zimmermann, A., Schmidt, R., & Müller, S. (2016). AI-powered video interviewing: Analyzing candidate traits. *Journal of Applied Psychology*, 101(8), 1456–1470.

Appendix

Semi-Structured Interview Guide

Designation: ____

Industry: ____

Section 1: Participant Background & General Use of AI in Recruitment

1. Can you describe your role in recruitment and your experience with AI-powered tools?
2. How does your organization integrate AI into the hiring process?
3. Which specific AI tools or platforms do you currently use for recruitment, and what functions do they serve?

Section 2: Bias Evaluation

4. Do you believe AI tools reduce biases in hiring? If so, how?
5. Have you observed instances where AI tools introduced or amplified biases?
6. Can you provide examples where AI has helped mitigate biases, or conversely, where it may have reinforced biases?
7. What are some potential challenges to ensuring fair hiring practices with AI recruitment tools?

Section 3: Human-AI Collaboration

8. What aspects of recruitment do you think AI handles better than humans?
9. Where do human recruiters outperform AI?

Section 4: Challenges & Ethical Concerns

10. What limitations have you encountered while using AI recruitment tools?
11. What steps do you take to ensure transparency and fairness when using AI in recruitment?

Section 5: Future Optimizations

12. What improvements would you suggest to make AI tools more effective in reducing bias?
13. How do you envision the future of AI in recruitment?