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Assessing the Impact of AI-Powered Recruitment on Operational Efficiency and Workforce Diversity in Zimbabwe's Coal Mining Sector

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Abstract
This study sought to assess the impact of AI-powered recruitment on operational efficiency and workforce diversity in Zimbabwe's coal mining sector. The study was guided by a pragmatism research philosophy; hence a mixed methodology paradigm was adopted. A sequential explanatory research design was employed. A target population of thirty participants participated in the study. Since the population was small, all thirty participants were considered into the sample through census sampling. To gather quantitative data, a questionnaire was employed, followed by interviews with 5 HR Directors who were purposively sampled. Quantitative data was gathered and analysed using content analysis method while qualitative data was analysed thematically. The study found that AI recruitment tools reduce time involved in hiring, improves new hire retention, reduces recruitment costs and improves the speed of candidate feedback, hence a positive impact on operational efficiency. Besides, the study found that AI tools help mitigate unconscious human bias in candidate shortlisting, thereby enhancing workforce diversity. In light of these findings, the study recommends that coal mining companies in Zimbabwe should embrace AI recruitment away from traditional recruitment methods for success towards job-relevant skills and predictive cognitive assessments that have been validated for non-discriminatory outcomes. The study also recommends that coal mining companies in Zimbabwe should move away from unstructured interviews to highly structured, competency-based interviews using consistent scoring rubrics that are not influenced by the AI's initial ranking in order to neutralize both human and algorithmic bias.

Keywords: Artificial intelligence, recruitment, operational efficiency, workforce diversity

1. Introduction and background

The widespread integration of artificial intelligence (AI) technologies has considerably transformed the modern work environments, globally (Murire, 2024; Soulami et al., 2024; Jarrahi & Sutherland (2019); Al Naqbi et al., 2024 & Brynjolfsson et al., 2023). Chilunjika et al., 2022) define Artificial Intelligence as the ability of a digital computer or computer-controlled robot to perform tasks associated with intelligent beings. It constitutes a collection of programs, algorithms, systems, and machines designed to mimic human cognitive processes, marking a revolutionary shift in organizational decision-making, particularly during recruitment processes (Mamela, 2021; Chilunjika et al., 2022). This technology necessity has quickly progressed from being implemented experimentally to being an essential part of the strategic HRM function. According to Arati, et al (2024), AI has a significant and indisputable immediate, quantifiable impact on talent acquisition on a global scale; hence its tangible and measurable benefits are what is driving its quick adoption, globally.

According to Baker et al., (2020), the integration of AI-powered recruitment within Britain presented a transformative opportunity to enhance operational efficiency and improve workforce diversity. Patil & Mhatre (2021) acknowledged that the traditional recruitment methods that were used in the British coal mining industries exhibited biases and inefficiencies, the implementation of AI tools streamlined applicant assessment processes, provided data-driven insights, and minimized human biases in hiring decisions. Similarly, AI technology facilitated streamlined recruitment processes in Nigeria by automating candidate screening and enabling unbiased decision-making through algorithmic assessments (Okoye & Eze, 2021; Akinyemi & Adeola, 2022). Ali et al., (2020) weighed in saying the adoption of AI has potential for improved efficiency not only reduces time-to-hire but also enhances the overall quality of the recruitment process. More so, Makhura et al., (2020) and Smith & Cummings, (2022) noted that the use of AI technology proved important in South Africa, where historical inequities necessitate proactive efforts to foster inclusivity across gender and ethnic lines. As was noted by Chigora & Chuma (2020), Zimbabwe seeks to revitalize its mining industry amidst economic fluctuations and in that regard, the introduction of AI could facilitate a more inclusive approach by attracting a diverse talent pool that reflects the nation’s demographics. Furthermore, AI's ability to analyze large datasets can help identify skill gaps and optimize workforce planning, thereby aligning talent acquisition with industry needs (Chiparauskas & Nyoni, 2022; Moyo & Ndebele, 2021). This study aims to explore the dual impact of AI on operational efficiency and diversity, providing insights into the transformative potential of technology in reshaping recruitment practices in Zimbabwe's mining sector.

Recent studies suggest that many organisations often use unscientific recruitment methods, including the widespread engagement in nepotism (Chilunjika, et al., 2022; Nugent & Scott-Parker., 2022 & Vrontis, et al., 2023). Such subjectivity in hiring processes directly contributes to the hiring of unsuitable candidates (Nugent & Scott-Parker., 2022), resulting in sub-optimal employee performance capability, hence negatively affecting operational efficiency (Chilunjika, et al., 2022). Operational efficiency refers to the proficiency of a corporation to curtail the unwelcome and maximise resource capabilities so as to deliver quality products and services to customers (Kalluru & Bhat 2009). Implementing standardised, parameter-based AI screening platforms becomes more than a simple operational upgrade since it functions as a strategic institutional mechanism for gaining legitimacy and trust. In this regard, introducing the global potential of AI recruitment in Zimbabwe’s coal mining sector signals a unique nexus of urgent necessity for technological governance and underlying organizational constraint.

There is also growing pressure in Zimbabwe’s coal mining sector to address serious issues with workforce diversity (Binha, 2021). Workforce diversity refers to heterogeneity and differences among employees in an organization in terms of race, age, ethnicity, cultural background, physical abilities, religion, gender, sexual orientation, language, education, lifestyle, beliefs, appearance, and economic status (Choi & Rainey., 2010). Despite the Constitution of Zimbabwe providing for gender equality in employment, representation, and decision-making positions (Section 56(2), as well as the National Gender Policy, which aims for gender mainstreaming across all sectors, including the coal mining sector, workforce diversity is still, and in many ways, an intangible dream. For example, in Zimbabwe's coal mining sector, men still make up the majority of workers, despite women actively participating in artisanal and small-scale mining (Binha, 2021). In this regard, there is need for policy realignment and sector upgrades to increase women's participation in the sector. According to (Vrontis, et al., 2023), AI offers a technological mechanism to address workforce diversity mandates by expanding the talent pool and identifying candidates previously overlooked by conventional, potentially biased sourcing methods.

2. Statement of the problem

Zimbabwe's coal mining sector faces persistent operational inefficiencies, productivity losses, and reduced competitiveness due to out-dated HR systems, nepotism, skills mismatches, and low workforce diversity. This study therefore investigates how AI-powered recruitment can enhance operational efficiency and improve workforce diversity in the sector.

3. Research objectives

This study was guided by the following research objectives;

- To investigate the willingness of HR professionals to adopt AI recruitment technologies in Zimbabwe's coal mining sector.
- To evaluate the effectiveness of AI-powered recruitment tools in helping coal mining companies in Zimbabwe select qualified candidates.
- To develop a framework for integrating AI recruitment tools that enhances efficiency and promotes workforce diversity in the coal mining sector.

4. Theoretical framework

This study was guided by a dual theoretical framework, hence a Resource-Based View and Institutional Theory were adopted. The Resource-Based View served as the primary lens for evaluating operational efficiency, while the Institutional Theory assisted in analysing workforce diversity.

4.1 Resource-Based View Theory

The Resource-Based View suggests that a sustained competitive advantage is achieved when an organization owns and controls resources and capabilities that are Valuable, Rare, Inimitable, and Non-substitutable (VRIN) (Nyamubarwa, et al., 2013). Since employees in the Zimbabwe's coal mining industry are treated as a valuable, rare, and inimitable resource, whose deployment is critical for achieving organizational objectives, AI recruitment is theorized as the superior strategic mechanism to acquire and secure this valuable human capital. Besides, the Resources-Based View contends that efficiency is driven by the Quality of Hire (QoH), which reduces risks and maximize returns in this capital-intensive sector (Bhorat, et al, 2025 & Nyamubarwa, et al, 2013), while poor selection leads to suboptimal performance (Bhorat, et al, 2025). In this regard, AI recruitment enhances operational efficiency by automating mundane administrative tasks and using predictive analytics to forecast a candidate's success in a role before commitment, thereby improving Quality of Hire. Given that the mining sector needs specialized skillsets and adaptability to fully capitalize on Industry 4.0 technologies (Mpofu & Nemashakwe, 2023), this theory argues that if AI recruitment successfully identifies and recruits high-performing, niche-skilled candidates, a rare pool, this superior talent acquisition capability becomes a source of competitive advantage that is difficult for rival firms to imitate. In this regard, the strategic deployment of AI recruitment is treated as an organizational capability that optimizes the entire talent pipeline, thereby moving the HR function from administrative support to a strategic value-driver.

4.2 Institutional Theory

The Institutional Theory focuses on how organizations conform to external rules, norms, and pressures to gain legitimacy and secure resources (Mpofu & Nemashakwe, 2023); hence it is critical for analysing the non-market and ethical dimensions of AI adoption. Coal mining firms face mandatory external pressures, such as the Constitution of Zimbabwe, which requires gender equality in employment and representation. In this regard, AI recruitment is viewed as a technological tool to comply with these institutional pressures by objectively expanding the talent pool and mitigating human bias, thereby directly addressing the sector's workforce diversity issues which have remained unresolved for so long. However, the use of any algorithm must be viewed with caution due to the risk of algorithmic bias, where historical data, from a male-dominated or nepotistic environment, reinforces existing inequalities (Soleimani, et al., 2025), hence the Institutional Theory helps in analysing the ethical governance required. In this regard, organizations should monitor and adjust AI systems to ensure transparency, fairness, and freedom from bias in alignment with local legal and social norms. Finally, local organizations face implementation barriers for HR technology, including inadequate funding, lack of required staff competencies, and insufficient management support (Gondo, et al., 2018); hence the Institutional Theory helped in measuring how these institutional barriers temper the global promises of AI efficiency when applied to the resource-constrained operational reality of the Zimbabwe's coal mining sector.

5. Conceptual framework

A conceptual framework for this study was structured into three components namely; independent, moderating, and dependent variables. The framework represents the relationships between AI recruitment technology, sector specific factors of the Zimbabwe's coal mining sector, and the resulting outcomes of operational efficiency and workforce diversity.

Figure 1 below depicts a conceptual framework developed by the researchers during the study.

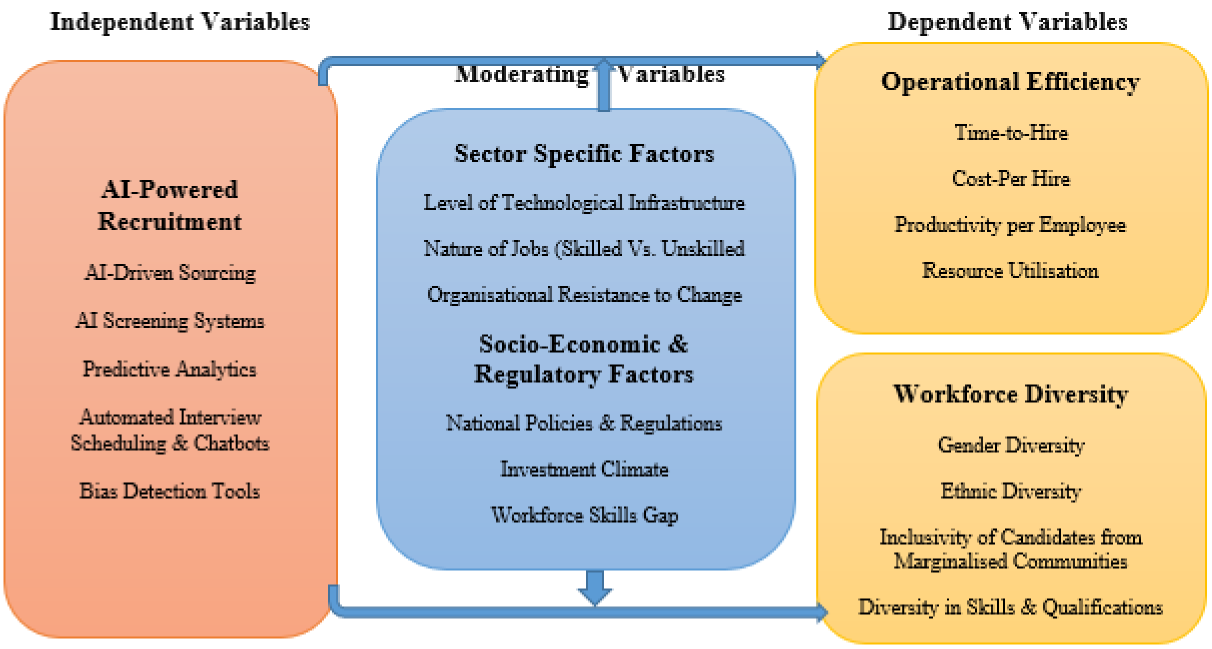

Fig 1. Conceptual framework: (Source: Researchers' Own, 2026)

As depicted in Figure 1 above, AI-powered recruitment serves as the primary intervention, encompassing various tools such as AI-driven sourcing, screening systems, predictive analytics, automated interview scheduling, chatbots, and bias detection features. Dependent variables are outcomes that AI-powered recruitment is expected to influence. Depended variables include operational efficiency workforce diversity. Operational efficiency measures aspects like time-to-hire, cost-per-hire, resource utilisation and productivity per employee while workforce diversity focus on representation of a varied mix of employees such as gender, ethnic, skills, qualifications and inclusivity of candidates from marginalized communities. However, moderating variables include sector-specific factors and socio-economic and regulatory factors. Sector-specific factors include the level of technological infrastructure, nature of jobs and organizational resistance to change while socio-economic and regulatory factors include national policies and regulations, investment climate, and workforce skills gap among others.

6. Review of related literature

6.1 Willingness of HR professionals to adopt AI recruitment technologies in Zimbabwe's coal mining sector

The willingness of HR professionals to adopt AI recruitment technologies presents a nuanced picture, partly showing a strong recognition of AI's potential benefits alongside significant barriers and concerns (Mohamed et al. 2025); Johar. 2024) & Kaushal & Ghalawat., 2023). According to Kaushal & Ghalawat (2023), HR professionals view AI as a 'double-edged sword'. The scholars strongly recognize AI's potential in automating routine tasks such as resume scanning, but also fear a 'depletion of human judgment' and potential ethical breaches in sensitive decision-making. According to Mohamed et al. (2025), majority of HR professionals are increasingly willing to adopt AI, primarily due to the perceived benefits it offers, but are afraid of the complexity of its implementation. Perceived benefits for using AI-recruitment include its ability to automate repetitive HR tasks including resume screening, candidate sourcing, and interview scheduling (Kaushal & Ghalawat., 2023); improved decision-making and quality of hire (QoH) (Johar., 2024), and mitigation of bias (Oman, et al., 2024). Reduction in time, for example, allows HR staff to shift their focus to more strategic and human-centric activities, such as relationship building and fostering organizational culture. Further, Ore & Sposato (2022) states that AI-powered Applicant Tracking Systems (ATS) use sophisticated algorithms to rank candidates based on a multi-faceted analysis of skills and experience which enhances quality for hire. However, while majority of organisations believe that adopting AI is essential, a number of limitations significantly restrict the deployment and upkeep of these intricate systems, hence creating a willingness-capacity conundrum. Various studies has shown that major obstacles to the adoption of HR AI, include insufficient money, lack of support from senior management, and lack of HR competences and understanding among employees on how to use AI systems efficiently (Mohamed et al. (2025); Johar., 2024) & Kaushal & Ghalawat., 2023). This situation risks the accumulation of technology debt, where non-customized, high-tech solutions fail to integrate locally, and ultimately undermining efficiency.

6.2 The effectiveness of AI-powered recruitment tools in helping coal mining companies in Zimbabwe select qualified candidates

The effectiveness of AI-powered recruitment tools in selecting qualified candidates has been reported to be overwhelmingly positive regarding efficiency and speed, despite presenting a complex, contentious debate concerning predictive accuracy, fairness, and quality of hire when compared to human-led processes (Wazna, 2024). Primarily, the irrefutable effectiveness of AI recruitment tools lies in their ability to automate and streamline the initial stages of the hiring process (Minbaeva., 2021) and instantly filtering and ranking candidates based on qualifications, skills, and experience (Albert, 2019 & Chen, 2023). This, according to Wazna (2024), enables HR professionals to shift their focus to more strategic functions. Further, AI allows for the optimized use of HR data by scanning vast external databases, for example, through LinkedIn and internal Applicant Tracking Systems (ATS) much faster and more accurately than humans, hence broadening the candidate pool and improving the quantity and reach of talent sourcing (Kshetri, 2021). However, while AI is fast, a key limitation is in its inability to entirely replace human recruiters, particularly in assessing soft skills, cultural fit, and candidate potential (Wazna, 2024 & Chen, 2023). Mori et al. (2024) argues that the complexity of interpreting nuanced human communication, essential for predicting team cohesion and long-term organisational success, often requires human judgment. The most significant area of contention regarding AI's effectiveness revolves around its unsubstantiated ability to reduce bias versus the risk of perpetuating it. According to Garg et al. (2023), AI uses objective, data-driven criteria, reducing the influence of unconscious human bias related to gender, race, or age during the initial screening. However, critics argue that AI algorithms are only as objective as the historical data they are trained on (Dessler, 2020). Thus, if past data reflects human discrimination, the AI will embed and exaggerate this bias, leading to unfair and discriminatory outcomes that may violate ethical and legal standards (Prikshat et al., 2023; Barocas & Selbst, 2016). Further, lack of transparency and ability to explain why certain decisions have been taken in 'black box' algorithms hinders the ability of HR professionals to audit and justify hiring decisions, hence compromising trust and accountability (Chilunjika et al., 2022). In this regard, for AI to be truly effective in selecting qualified candidates, a balanced approach is essential.

6.3 Framework for integrating AI recruitment tools that enhances efficiency and promotes workforce diversity in the coal mining sector

Integrating AI recruitment tools effectively to enhance operational efficiency, while promoting workforce diversity, requires a robust, multi-dimensional framework that moves beyond mere technological implementation. A highly relevant framework for achieving this dual objective is the Ethical, Accountable, and Transparent (EAT) framework (Dutta et al., 2025). This framework synthesizes insights from the Technology-Organization-Environment (TOE) model (Tornatzky & Fleischer, 1990) for organizational readiness and the need for Algorithmic Accountability (Barocas & Selbst, 2016). The EAT framework operates across three core, interdependent pillars, ensuring that AI is used as an augmentative tool for operational efficiency and a reparative tool for workforce diversity. The Ethical (E) pillar focuses on proactively mitigating bias and ensuring fairness regarding algorithmic bias (Dessler, 2020; Prikshat et al., 2023). In this regard, there is need to conduct rigorous, mandatory audits of the historical recruitment data used to train the AI models. O'Neil (2016), in Weapons of Math Destruction, warns that models trained on biased data will merely automate and scale up past human prejudice, hence HR professionals must actively vet the data for discriminatory patterns. Further, Kleinberg et al. (2017) advocate for the need to implement fairness metrics by adopting formal definitions of fairness, such as Disparate Impact (DI) or Equal Opportunity Difference (EOD), and monitor these metrics across demographic groups before and after implementation. According to Prikshat et al (2023), the Accountable (A) pillar ensures human responsibility remains central, addressing the fear of the 'black box' and maintaining the human touch. This pillar establishes a human review threshold by mandating all candidates who are flagged for exclusion by the AI, or all candidates who fall within a certain low-confidence score range, are automatically subjected to a human-led review by trained HR professionals, hence minimizing the risk of qualified diverse candidates being screened out unjustly. Harney & Collings (2021) stress the need for a 'human-in-the-loop' model, arguing that AI should augment human judgment, not substitute it, especially in complex, high-stakes decisions like hiring. The Accountable (A) pillar also focuses on continuous monitoring and feedback loops by regularly auditing AI's impact on actual diversity and performance outcomes, using retention rates and internal performance reviews as feedback data to retrain and refine the model iteratively. Finally, the Transparent (T) pillar builds trust among stakeholders, candidates, employees, and regulators, by offering clarity on the AI's function. This pillar focuses on explainable AI adoption by implementing AI tools that can provide justification for their ranking decisions, rather than relying on opaque models (Dessler, 2020). Thus, HR management must be able to explain to a candidate why they were filtered out. According to Chilunjika et al. (2022) the shift towards explainable AI is critical, hence a lack of transparency erodes trust and makes it impossible to detect unfair decisions. Minbaeva (2021) posit that the ERT framework is designed to maximize the operational efficiency gains of AI while promoting workforce diversity by institutionalising fairness and accountability at every stage of the recruitment process.

While AI is employed to mitigate human bias and ensure a fairness during recruitment, the introduction of complex algorithms necessitates caution. Concerns about AI's ability to lessen bias are still prevalent, globally, and HR experts moderately support its impact on workforce diversity (Prikshat et al., 2023). This potential for algorithmic bias, where historical data from a male-dominated industry is used to train the system, hence reinforcing existing inequalities, demands careful ethical scrutiny. Therefore, for AI to function as a beneficial tool in recruitment matters, organizations must be able to monitor and adjust algorithms to ensure fairness and compliance. This study sought to assess the potential of AI in driving operational efficiency, as measured by enhanced quality of hire (QoH) and speed, as well as fostering workforce diversity.

7. Methodology

This study adopted a pragmatism research philosophy; hence a mixed methodology paradigm was employed (Fischler, 2021; Creswell, 2014). This assisted in gathering reliable results using both quantitative and qualitative methods. A sequential explanatory research design was adopted in presenting and analysing both quantitative and qualitative data. Gathering of qualitative data was informed by quantitative analysis (Fischler, 2021). Gathered sets of data were analysed and interpreted separately, but presented concurrently as illustrated in Figure 1 below.

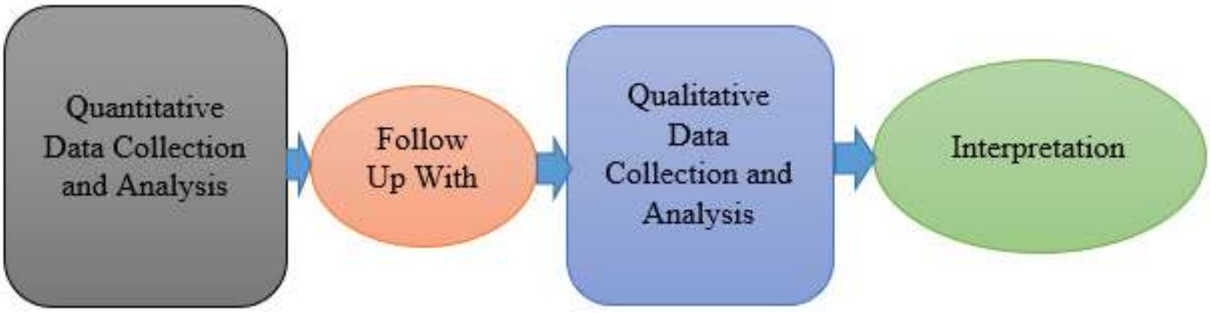

Fig 2. Sequential explanatory research design (Source: Fischler, A.S, 2021)

A target population of 30 HR professionals from 10 coal mining companies operating in Hwange District was considered. Since the population was small, data from all the 30 participants was considered for quantitative analysis through census sampling. All the 30 participants were served with questionnaires which they completed and returned for analysis. Quantitative data was presented on graphs and tables.
For purposes of qualitative data analysis, five (5) HR Directors, each purposively selected from coal mining companies in Hwange District were interviewed. An in-depth interview guide was tested for validity using the Lawshe`s 1975 model of assessing content (Kurauone et al., 2021) (Appendix III). Ten (10) experts evaluated the content using the Content Validity Ratio and a minimum of 0.78 was considered. All items that passed the minimum score were included in the interview guide.

$$\mathrm{CVR} = \frac{(\mathrm{n_e} - 0.5\mathrm{N})}{0.5\mathrm{N}}$$

Where **CVR** is the Content Validity Ratio, $\mathbf{n_e}$ = the number of experts observing the content as relevant to be researched, and **N** = the total number of experts in the panel.
Data collected was subjected to strict confidentiality while the anonymity of respondents was guaranteed. Besides, the study was conducted and presented in an honest, transparent and accurate manner to make sure that findings were not falsified or misrepresented (Resnik, 2015).

8. Results

Results on the impact of AI-powered recruitment on operational efficiency and workforce diversity in Zimbabwe's coal mining sector are presented below.

8.1 Results on the use of AI recruitment tools in Zimbabwe' coal mining sector

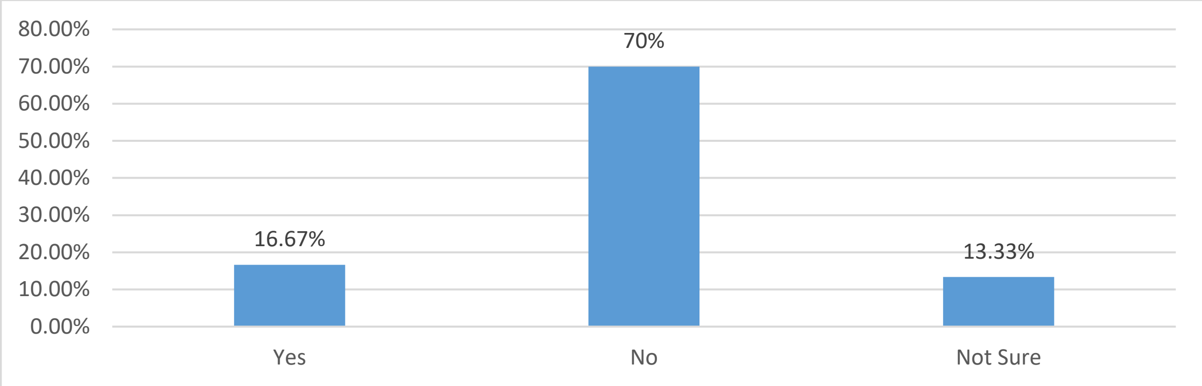

Figure 3: Results on the use of AI recruitment tools in Zimbabwe' coal mining sector

As depicted in Figure 3 above, results from the study show that while there is significant adoption of AI tools for recruitment, majority of organisations in Zimbabwe's coal mining sector are yet to adopt AI-powered recruitment, instead they are opting for unscientific traditional recruitment methods, including the widespread engagement in nepotism, which contributes to the hiring of unsuitable candidates, resulting in sub-optimal employee performance capability, hence negatively affecting operational efficiency and workforce diversity. During interviews interview 1 had this to say;
'Our organisation is not using any AI tools for recruitment purposes. The company is heavily reliant on unscientific methods of recruitment.'

8.2 Results on the benefits of using AI-tools during recruitment

Responses	**Frequency**	**Response Rate %**
Mitigation of bias	12	40
Enhances quality of hire (QoH)	8	26.67
Improves decision-making	4	13.33
Automates repetitive HR tasks	6	20
Total	**30**	**100**

Table 1: Results on the benefits of using AI-tools during recruitment

As presented in Table 1 above, the study established a number of benefits that accrue from the use of AI-powered tools. Notably, mitigation of bias was the most mentioned benefit of using AI tools during recruitment. Besides, respondents mentioned other benefits including quality of hire, improved decision-making and automating repetitive HR tasks including resume screening, candidate sourcing, and interview scheduling, ultimately reducing time of hiring. Interviewees also echoed similar responses during the study. For example, interviewee 2 said:
'The use of AI-tools for recruitment purposes has a number of benefits that accrue to the organisation including mitigation of bias, quality of hire, improved decision-making among others.'

8.3 Results on the willingness of HR professionals in Zimbabwe's coal mining sector to adopt AI recruitment technologies

Statement	**SD**	**D**	**N**	**A**	**SA**

I am personally willing to invest time and effort to learn and use AI tools.	1 (3.33)	2 (6.67)	4 (13.33)	6 (20.0)	17 (56.67)
I believe AI can significantly reduce the administrative workload of the initial screening process.	1 (3.33)	3 (10.0)	2 (6.67)	9 (30.0)	15 (50.0)
The cost of AI solutions is a major barrier to adoption in our organization.	0 (0)	3 (10.0)	3 (10.0)	11 (36.67)	13 (43.33)
Lack of specialized IT skills to manage/integrate AI is a concern for me.	1 (3.33)	2 (6.67)	6 (20.0)	10 (33.33)	11 (36.67)
I am concerned that AI may replace human recruiters entirely.	0 (0)	2 (6.67)	3 (10.0)	9 (30.0)	16 (53.33)
I would be willing to adopt AI if clear ethical guidelines were provided by the government/industry.	0 (0)	3 (10.0)	5 (16.67)	6 (20.0)	16 (53.33)

Table 2: Results on the willingness of HR professionals in Zimbabwe's coal mining sector to adopt AI recruitment technologies.

Results from the study suggest a resounding willingness of HR professionals in Zimbabwe's coal mining sector adopt AI-powered recruitment technologies. Majority of the respondents strongly agreed that they are willing to invest time and effort to learn and use AI tools during recruitment processes. They also believe that AI can significantly reduce the administrative workload of the initial screening process. This was also echoed by Oman, et al. (2024) who whose argued that by reducing administrative workload, AI allows HR staff to shift their focus to more strategic and human-centric activities, such as relationship building and fostering organizational culture. Despite their willingness to adopt AI-powered recruitment, cost of AI solutions was overwhelmingly reported as a major barrier to its adoption in most organizations in the sector. Besides, lack of specialized IT skills to manage/integrate AI was reported as a concern by majority on participants. Further, the study found that despite most of HR professionals being willing to embrace AI-powered recruitment, they are also concerned that AI may replace human recruiters entirely. However, despite all these concerns noted, the study established that HR professionals were willing to adopt AI if clear ethical guidelines were provided by the government/industry.

8.4 Results on the effectiveness of AI-powered recruitment tools in helping coal mining companies in Zimbabwe select qualified candidates

The study sought to evaluate the effectiveness of AI-powered recruitment tools in helping coal mining companies in Zimbabwe select qualified candidates. This was measured by assessing the impact of AI recruitment tools on operational efficiency and workforce diversity.

8.4.1 Results on the impact of AI recruitment tools on operational efficiency

Statements	SD	D	N	A	SA
AI tools reduces time involved in hiring.	1 (3.33)	3 (10.0)	5 (16.67)	8 (26,67)	13 (43.33)
AI tools are accurate in matching technical job requirements.	0 (0)	2 (6.67)	3 (10.0)	7 (23.33)	18 (60.0)

AI tools improves new hire retention rate.	0 (0)	2 (6.67)	6 (20.0)	6 (20.0)	16 (53.33)
AI tools reduces recruitment cost per hire.	1 (3.33)	3 (10.0)	3 (10.0)	6 (20.0)	17 (56.67)
AI tools improves the speed of candidate feedback.	0 (0)	3 (10)	5 (16.67)	7 (23.33)	15 (50.0)

Table 3: Results on the impact of AI recruitment tools on operational efficiency.

Results from the study shows that AI recruitment tools have a significant impact on operational efficiency. For example, majority of participants indicated that AI tools reduces time involved in hiring. This is also echoed by Kaushal & Ghalawat (2023). Also, despite some respondents claimed that AI tools are accurate in matching technical job requirements, a combined 83.33% of the participants indicated that AI tools are good in matching technical job requirements. The study found that AI recruitment tools improves new hire retention, reduces recruitment costs and improves the speed of candidate feedback, hence implying a positive impact on operational efficiency.

8.4.2 Results on the impact of AI recruitment tools on workforce diversity

Statements	SD	D	NS	A	SA
AI tools can help mitigate unconscious human bias in candidate shortlisting.	0 (0)	3 (10.0)	4 (13.33)	6 (20.0)	17 (56.67)
The AI systems we use (or might use) are trained on data that fairly represents diverse candidate demographics in Zimbabwe.	1 (3.33)	3 (10.0)	3 (10.0)	5 (16.67)	18 (60.0)
I am concerned about algorithmic bias unintentionally discriminating against groups like women or minorities in a historically male-dominated sector like mining.	0 (0.0)	3 (10.0)	5 (16.67)	6 (20.0)	16 (53.33)
AI is effective in helping us identify and reach talent from underrepresented groups.	0 (0)	3 (10.0)	4 (13.33)	9 (30.0)	14 (46.67)

Table 4: Results on the impact of AI recruitment tools on workforce diversity

Results from the study revealed a strong impact of AI recruitment tools on workforce diversity. As indicated in Table 4 above, majority of participants stated that AI tools can help mitigate unconscious human bias in candidate shortlisting. These findings were also echoed by Garg et al. (2023) who stated that AI uses objective, data-driven criteria which then reduces the influence of human bias related to gender, race, or age during the initial screening. Majority of the participants indicated that AI systems used for recruitment are trained on data that fairly represents diverse candidate demographics as well as effectively in helping identify and reach talent from underrepresented groups. However, despite these positive impacts, the study found that HR professional are concerned about algorithmic bias, hence the unintentional discrimination against groups like women or minorities.

8.5 Results on a framework for integrating AI recruitment tools that enhances efficiency and promotes workforce diversity in the coal mining sector

The study sought to develop a framework for integrating AI recruitment tools that enhances efficiency and promotes workforce diversity in the coal mining sector. The study did this by recommending a single most critical component for ensuring ethical and effective AI adoption as well as suggesting ways of balancing efficiency goals with diversity goals using AI recruitment framework.

8.5.1 The single most critical component for ensuring ethical and effective AI adoption

Responses	**Frequency**	**Response Rate (%)**
Mandatory human oversight	6	20
Transparency	3	10
Regular bias audits of the AI algorithms and training data	19	63.33
High-level data security and privacy protocols	2	6.67
Total	**30**	**100**

Table 5: The single most critical component for ensuring ethical and effective AI adoption.

As depicted in Table 5 above, results shows that while all the suggested components are essential for a robust AI strategy, the most critical component for insuring ethical and effective AI adoption is regular bias of the AI algorithms and training data. This consistent with Nawaz, N. (2020) who argued that while data security protects the person, for example, bias audits protects the integrity of the entire hiring system. During interviews majority of the interviewees echoed a similar response arguing that AI in recruitment is uniquely prone to 'algorithmic bias,' where the software inadvertently learns and replicates human prejudices such as gender, race, or age bias found in historical hiring data, hence without regular audits, an AI could systematically reject qualified candidates from minority backgrounds without the HR team ever realizing why (Prikshat et al., 2023).

8.5.2 Balancing efficiency goals with diversity goals using AI recruitment framework

Responses	**Frequency**	**Response Rate (%)**
Efficiency should be the absolute priority	3	10
Efficiency should be the priority, but diversity must be considered	6	20
Both should be given equal priority	16	53.33
Diversity should be the priority, but efficiency must be considered	3	10
Diversity should be the absolute priority	2	6.67
Total	**30**	**100**

Table 6: Balancing efficiency goals with diversity goals using AI recruitment framework

As presented in Table 6 above, despite varied suggestions, results revealed that both efficiency and diversity goals should be given priority in a new AI recruitment framework. Thus, participants noted that in the current research landscape, efficiency and diversity are no longer seen as a 'trade-off' where one must be sacrificed for the other, but instead they are viewed as mutually reinforcing goals. They argued that if a system is purely optimized for speed (efficiency), it often relies on 'short-cut' patterns from historical data and leads to algorithmic bias, hence ultimately makes the system ineffective because it filters out high-potential talent from diverse backgrounds (O'Neil, 2016). On the other hand, if diversity measures are purely manual and slow down the hiring process, the organization loses top talent to faster competitors. Thus, a well-designed AI framework uses efficiency to handle high volumes of data while simultaneously using bias-mitigation algorithms to ensure that the 'fast' decisions are also 'fair' decisions.

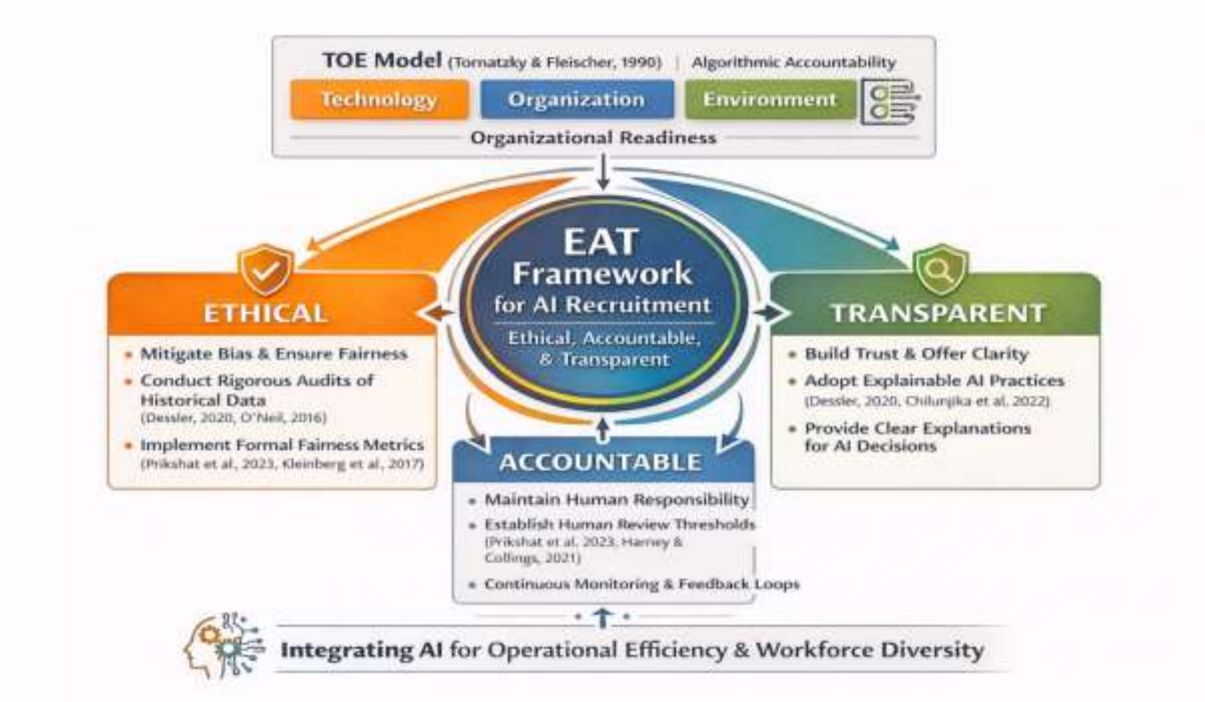

Figure 2: EAT Framework: Authors' own illustration.

The EAT framework is a set of guiding principles designed to ensure that Artificial Intelligence used in hiring remains fair, responsible, and understandable. As companies move away from manual resume screening toward automated systems, EAT acts as a safeguard against 'black box' algorithms that might inadvertently bake in human bias. In this regard, Ethical AI ensures that the technology treats every candidate with dignity and fairness. The primary goal here is to eliminate algorithmic bias. This can be achieved by ensuring that the AI does not favor specific demographics (gender, race, age) based on historical data patterns that reflect past prejudices. Besides, there is need to ensure that the AI interface is usable for candidates with disabilities, for example, screen reader compatibility for AI-driven assessments. The systems should ensure privacy by protecting candidate data and ensuring it is only used for the specific purpose of recruitment. Accountability means that humans, not just the software, are responsible for the decisions made during the hiring process. In this regard, AI should assist, but not replace, human recruiters, hence final hiring decisions should always involve human oversight. Besides, companies must frequently test their AI models to ensure they aren't drifting toward biased outcomes over time. Candidates should also have a way to challenge an AI-driven decision or request a human review if they feel the process was flawed. Transparency is about clarity. Candidates and recruiters alike should understand why the AI is making certain recommendations. There is need to inform candidates upfront that an AI system is being used to evaluate their application. The system should also have the ability to explain the logic behind a score. For example, instead of just saying 'Candidate X is a 9/10', the system should indicate that 'Candidate X was ranked highly due to 5 years of Python experience and leadership keywords. Finally, the system should provide clear information on what data points the AI considers and how it weighted them.

11. Implications of the study

The implication of this research is that while embracing of AI-recruitment tools in Zimbabwe's coal mining sector has the potential to considerably boost operational efficiency by streamlining the hiring process, it also introduces multifaceted ethical challenges concerning workforce diversity. Thus, while efficiency gains could lead to reduced costs and improved quality of hire, organisations should carefully balance against the risk of algorithmic bias, where AI systems trained on historically male-dominated data in the mining sector could unintentionally maintain existing gender, age, or background biases, thereby undermining efforts to achieve a more diverse workforce. Besides, the reliance on advanced AI technology highlights the need for significant investment in digital skills training for HR professionals and a focus on data governance and transparency to ensure ethical, fair, and equitable recruitment outcomes in Zimbabwe's coal mining sector.

12. Conclusions

Considering the findings, the study concludes that AI-powered tools lead to a measurable reduction in time-to-hire and cost-per-hire. The streamlining of the hiring process allows HR staff to focus on more strategic human resource initiatives. The study also concludes that the use AI algorithms result in an improved job-candidate fit, potentially leading to higher employee retention and productivity in a challenging mining environment. Further, the study concludes that AI has the potential to reduce human bias since it carries limited risk of algorithmic bias. For example, if the AI models are trained on historical data from the predominantly male-dominated Zimbabwean coal mining sector, they will likely perpetuate existing biases, leading to an unintentional exclusion of qualified female candidates or individuals from underrepresented groups, thus undermining efforts to improve workforce diversity. The successful adoption of AI is conditional on establishing robust ethical and governance frameworks. The study concludes that human oversight, regular algorithm audits, and transparency in how AI makes hiring decisions are crucial to ensure fairness, accountability, and legal compliance. The study concluded that there is a presence of barriers to full-scale AI adoption, including the high initial cost of procuring and integrating advanced AI systems, and a shortage of local HR professionals and IT staff with the requisite skills to deploy, manage, and audit these technologies effectively. The study concluded that the overall use of AI in recruitment is currently low or in its nascent stage, but that there is a strong perceived value and a clear case for strategic, phased implementation, particularly for high-volume or entry-level positions. Finally, the study concluded that AI is a double-edged sword for the coal mining sector, that is, a powerful driver of efficiency that requires proactive policy and ethical intervention to ensure it does not come at the expense of equitable and inclusive talent acquisition.

13. Recommendations

The study recommends that;

- Mining companies using AI recruitment tools should commission independent, third-party bias audits of their algorithms and these audits should specifically track the selection, shortlisting, and hiring rates across protected groups such as gender, age, and ethnicity to detect and correct algorithmic bias.
- Mining companies should move away from unstructured interviews to highly structured, competency-based interviews using consistent scoring rubrics that are not influenced by the AI's initial ranking in

order to neutralize both human and algorithmic bias as well as to systematically anonymise candidate resumes by removing protected attributes during the initial AI and human screening phases.
- Mining companies should shift AI assessment criteria away from historical proxies for success towards job-relevant skills and predictive cognitive assessments that have been validated for non-discriminatory outcomes.
- Companies must invest in mandatory training for HR staff, recruiters, and hiring managers on the mechanics and limitations of their specific AI tools, unconscious bias mitigation, and interpreting and challenging AI-driven insights.
- A collaborative approach between local Zimbabwean technological firms, universities, and mining companies to develop AI models trained on a diverse data-set specific to the local labour market, rather than relying solely on global models that may carry inherent biases from different labour backgrounds.
- Companies should be required to track and publicly report, internally or externally, on key diversity metrics across the entire recruitment funnel, including application rate, shortlisting rate, interview rate, offer rate, and acceptance rate for different demographic groups, ensuring the AI does not create a bottleneck at any stage.

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