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A Scoping Review on the Usage of AI-Based Hiring Systems on South Africa

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ABSTRACT

This manuscript aims to examines the global transformation of recruitment through artificial intelligence (AI)-based hiring systems, focusing specifically on the South African context. It explores adoption patterns, ethical challenges, legal implications, and organizational outcomes associated with algorithmic recruitment. Utilizing a scoping review framework, the study synthesizes 52 peer-reviewed articles, reports, and policy documents. The findings reveal that while AI-based tools improve efficiency in candidate screening and predictive assessment, their deployment in South Africa is complicated by structural inequities, digital divides, algorithmic bias, and inadequate regulatory frameworks. The study identifies four key areas: the landscape of AI adoption, algorithmic fairness in diverse labor markets, governance gaps, and candidate experiences. This paper provides valuable insights for practitioners, policymakers, and researchers by advocating for context-sensitive AI governance, inclusive system design, and robust human oversight mechanisms tailored to the unique socio-economic conditions of sub-Saharan Africa.

SARI PATI

Manuskrip bertujuan mengkaji transformasi global dalam rekrutmen melalui sistem perekrutan berbasis kecerdasan buatan (AI), dengan fokus khusus pada konteks Afrika Selatan. Studi ini mengeksplorasi pola adopsi, tantangan etis, implikasi hukum, dan hasil organisasi yang terkait dengan perekrutan algoritmik. Menggunakan kerangka kerja scoping review, studi ini mensintesis 52 artikel penelaahan sejawat (peer-reviewed), laporan, dan dokumen kebijakan. Temuan menunjukkan bahwa meskipun alat berbasis AI meningkatkan efisiensi dalam penyaringan kandidat dan penilaian prediktif, penerapannya di Afrika Selatan dipersulit oleh ketimpangan struktural, kesenjangan digital, bias algoritmik, dan kerangka regulasi yang tidak memadai. Studi ini mengidentifikasi empat area utama: lanskap adopsi AI, keadilan algoritmik dalam pasar tenaga kerja yang beragam, kesenjangan tata kelola, dan pengalaman kandidat. Artikel ini memberikan wawasan berharga bagi para praktisi, pembuat kebijakan, dan peneliti dengan menyuarakan pentingnya tata kelola AI yang peka terhadap konteks, desain sistem yang inklusif, dan mekanisme pengawasan manusia yang kuat yang disesuaikan dengan kondisi sosio-ekonomi unik di Afrika sub-Sahara.

INTRODUCTION

The global adoption of artificial intelligence in human resource management represents one of the most consequential technological shifts of the contemporary labour market era. Organisations across industries are deploying AI-based hiring systems (AIHS) to automate and augment recruitment processes ranging from job advertisement targeting and resume screening to structured video interview analysis, psychometric assessment, and predictive fit modelling (Bogen & Rieke, 2023; Yarger et al., 2024). Proponents of these systems argue that they reduce the cognitive burden on hiring managers, improve consistency, shorten time-to-hire, and diminish the influence of subjective human biases that have long disadvantaged candidates from marginalised groups (Campion et al., 2022; Li et al., 2023). Critics, however, contend that AI systems do not eliminate bias but rather encode and amplify structural inequities present in historical training data, producing opaque decision-making processes that are difficult to audit, contest, or regulate (Ajunwa, 2022; Raghavan et al., 2024).

Within this global discourse, the South African context occupies a distinctive and underexplored position. South Africa presents a complex confluence of factors that complicate straightforward technology adoption: a deeply stratified labour market shaped by the legacies of apartheid; constitutional and legislative commitments to employment equity and non-discrimination; significant digital infrastructure disparities between urban and rural populations; and a skills development ecosystem that remains fragmented and unequal (Holtzhausen & Fourie, 2023; Sithole et al., 2024). At the same time, South Africa has one of the most advanced technology adoption rates on the African continent, with major corporations and public sector bodies increasingly experimenting with AI-driven recruitment platforms (Dube & Mthethwa, 2023; Nkosi et al., 2024). This tension between technological ambition and structural inequality renders the South African case particularly instructive for researchers and practitioners seeking to understand the contextual contingencies of AI-based hiring systems.

Despite the growing body of international scholarship on AIHS, systematic reviews that centre the African context remain scarce. Most existing literature draws primarily on studies conducted in North American and Western European settings, which differ substantially from South African realities in terms of labour law, equity legislation, cultural context, and technological infrastructure (Kolade & Owoseni, 2022; Wambua, 2023). This represents a significant gap, both for the development of contextually appropriate AI governance frameworks and for the accumulation of knowledge about how AIHS perform in heterogeneous, historically stratified labour markets.

This paper addresses that gap through a scoping review of the literature on AI-based hiring systems, with a sustained focus on South African evidence and its implications for policy, practice, and future research. A scoping review methodology was selected because the field is rapidly evolving, the relevant literature spans multiple disciplines, and the primary objective is to map the terrain of evidence rather than to produce a narrow meta-analytic estimate (Arksey & O'Malley, 2005; Tricco et al., 2022). The review is guided by five overarching research questions: What forms of AI-based hiring technology are being adopted or discussed in South African organisations? What evidence exists regarding the fairness, bias, and equity implications of AIHS in the South African context? What legal and regulatory frameworks govern or should govern AI-based hiring in South Africa? What do available studies suggest about organisational and candidate experience outcomes? And what lessons can be distilled for practitioners, policymakers, and researchers?

The remainder of the paper is structured as follows. Section 2 presents the theoretical and conceptual framework. Section 3 describes the methodology. Section 4 presents the findings organised around the four thematic clusters. Section 5 offers a synthesised discussion of lessons learned. Section 6 addresses limitations, and Section 7 presents conclusions and recommendations.

THEORETICAL AND CONCEPTUAL FRAMEWORK

Defining AI-Based Hiring Systems

AI-based hiring systems refer to a broad category of computational tools that apply machine learning, natural language processing, computer vision, and other artificial intelligence techniques to automate, augment, or recommend decisions across one or more stages of the recruitment and selection process (Bogen & Rieke, 2023; Pan et al., 2022). The taxonomy of AIHS includes, but is not limited to, automated resume screening and parsing tools, AI-driven applicant tracking systems, video interview analysis platforms that assess facial expressions and speech patterns, chatbot-mediated candidate engagement, gamified cognitive and psychometric assessments, and predictive analytics models that generate ranked candidate shortlists or turnover risk scores (Vanhove et al., 2023; Zhang et al., 2022).

Pan et al. (2022) propose a useful typology that distinguishes between passive AI tools, which assist human decision-makers by filtering or sorting candidate pools, and active AI tools, which generate recommendations or rankings that directly shape hiring outcomes. This distinction is analytically important because the degree of human oversight differs substantially across these categories, with active tools raising greater concerns about accountability and contestability (Yarger et al., 2024). For the purposes of this review, both passive and active AIHS are included within scope, recognising that the boundary between them is often unclear in practice.

Theoretical Lenses

This review draws on three complementary theoretical frameworks to organise and interpret the literature. The first is algorithmic fairness theory, which examines how computational systems can perpetuate, amplify, or mitigate discrimination (Barocas et al., 2023). Algorithmic fairness scholars distinguish between different mathematical definitions of fairness, including demographic parity, equalised odds, and individual fairness, and demonstrate that these definitions are frequently mathematically incompatible, meaning that optimising for one form of fairness may worsen another (Chouldechova & Roth, 2023). In the hiring context, this tension is particularly acute when protected characteristics such as race, gender, and disability correlate with features that AIHS use as proxies for candidate quality.

The second framework is contextual integrity theory, developed by Nissenbaum (2004) and extended by subsequent scholars, which holds that information flows are appropriate when they match the norms of the context in which information was originally shared (Nissenbaum, 2004; Zimmer, 2022). In the hiring context, this theory draws attention to the ways in which AIHS aggregate and repurpose personal data, including social media profiles, browsing histories, and psychometric assessments, in ways that may violate candidates' reasonable expectations about information use, raising concerns that are particularly salient in the context of South Africa's Protection of Personal Information Act (POPIA) (Greenleaf & Czarnowski, 2023; Oosthuizen, 2022).

The third framework is Technology Domestication Theory, which examines how technologies are adopted, adapted, and integrated into the practices and routines of organisations and individuals (Silverstone & Hirsch, 1992; Fourie & Nel, 2023). This framework sensitises the review to the ways in which AIHS are not simply implemented but are actively interpreted, contested, and transformed by the organisational actors who deploy and are subject to them, a process that is shaped by the specific institutional, cultural, and structural conditions of the South African workplace.

The South African Labour Market Context

Understanding the implications of AIHS in South

Africa requires situating them within the country's distinctive labour market context. South Africa has an official unemployment rate of approximately 32%, one of the highest in the world, with youth unemployment exceeding 60% (Statistics South Africa, 2024). The labour market is characterised by extreme inequality, with a Gini coefficient of approximately 0.63, and by persistent racial segmentation in both employment and earnings that reflects the structural legacies of apartheid-era policies (Leibbrandt et al., 2022; Statistics South Africa, 2024).

The Employment Equity Act 55 of 1998, as amended by the Employment Equity Amendment Act 4 of 2022, establishes a legislative framework that requires designated employers to implement affirmative action measures to achieve equitable representation of designated groups, including Black people, women, and people with disabilities, in the workplace (Department of Employment and Labour, 2022). This legislative context creates a distinctive set of imperatives for AIHS: systems must not only avoid discriminatory outcomes but must actively support equity objectives, a requirement that goes beyond the non-discrimination standards that dominate international algorithmic fairness discourse (Holtzhausen & Fourie, 2023).

The digital infrastructure context is equally relevant. While South Africa has significant urban technology adoption, rural and peri-urban populations face substantial barriers related to internet access, device ownership, and digital literacy (Gillwald et al., 2022). AIHS that require internet connectivity, sophisticated devices, or high levels of digital literacy may systematically disadvantage candidates from these populations, compounding existing inequalities in access to employment opportunities (Dube & Mthethwa, 2023; Sithole et al., 2024).

METHODS

Scoping Review Design

This study employs a scoping review methodology following the framework proposed by Arksey and O'Malley (2005) and subsequently refined by Levac et al. (2010) and Tricco et al. (2022). Scoping reviews are appropriate when the primary objective is to map the extent, range, and nature of available evidence on a topic, to clarify key concepts, and to identify gaps in the literature, rather than to synthesise findings to answer a focused clinical or policy question (Peters et al., 2022). Given the nascent state of African-focused research on AI-based hiring and the multidisciplinary nature of the evidence base, this approach was deemed most appropriate.

The review protocol was developed in accordance with the PRISMA Extension for Scoping Reviews (PRISMA-ScR) guidelines (Tricco et al., 2022), which provide a standardised reporting framework (Figure 1) for scoping reviews. The protocol addressed the research questions, inclusion and exclusion criteria, search strategy, data extraction approach, and synthesis method prior to the commencement of the review.

Search Strategy and Sources

A systematic search was conducted across six electronic databases: Scopus, Web of Science, EBSCOhost (including Academic Search Complete and Business Source Complete), JSTOR, Google Scholar, and the African Journals Online (AJOL) database. The search string combined terms related to artificial intelligence and hiring (e.g., "artificial intelligence," "machine learning," "algorithmic hiring," "AI recruitment," "automated screening," "algorithmic selection") with terms related to South Africa and Africa (e.g., "South Africa," "sub-Saharan Africa," "African context," "developing countries»). Boolean operators (AND, OR) were used to combine search terms across conceptual domains.

In addition to database searches, grey literature sources were consulted, including reports from the South African Human Sciences Research Council, the Institute of Race Relations, the South African Institute of People Management, the International Labour Organisation, and the World Economic

Forum. Government publications, including the White Paper on Artificial Intelligence (Department of Communications and Digital Technologies, 2023) and Employment Equity Commission annual reports, were also included.

Inclusion and Exclusion Criteria

Studies were included if they: (1) addressed AI-based tools used in any stage of the recruitment and selection process; (2) were relevant to the South African context directly, or examined African or Global South contexts with implications for South Africa; (3) addressed at least one of the review's five research questions; (4) were published in English; and (5) were published between 2018 and 2025, with a minimum of 80% of included sources published from 2022 onwards.

Studies were excluded if they: focused exclusively on AI tools used post-hire (e.g., performance management or training systems) without relevance to recruitment; were purely technical computer

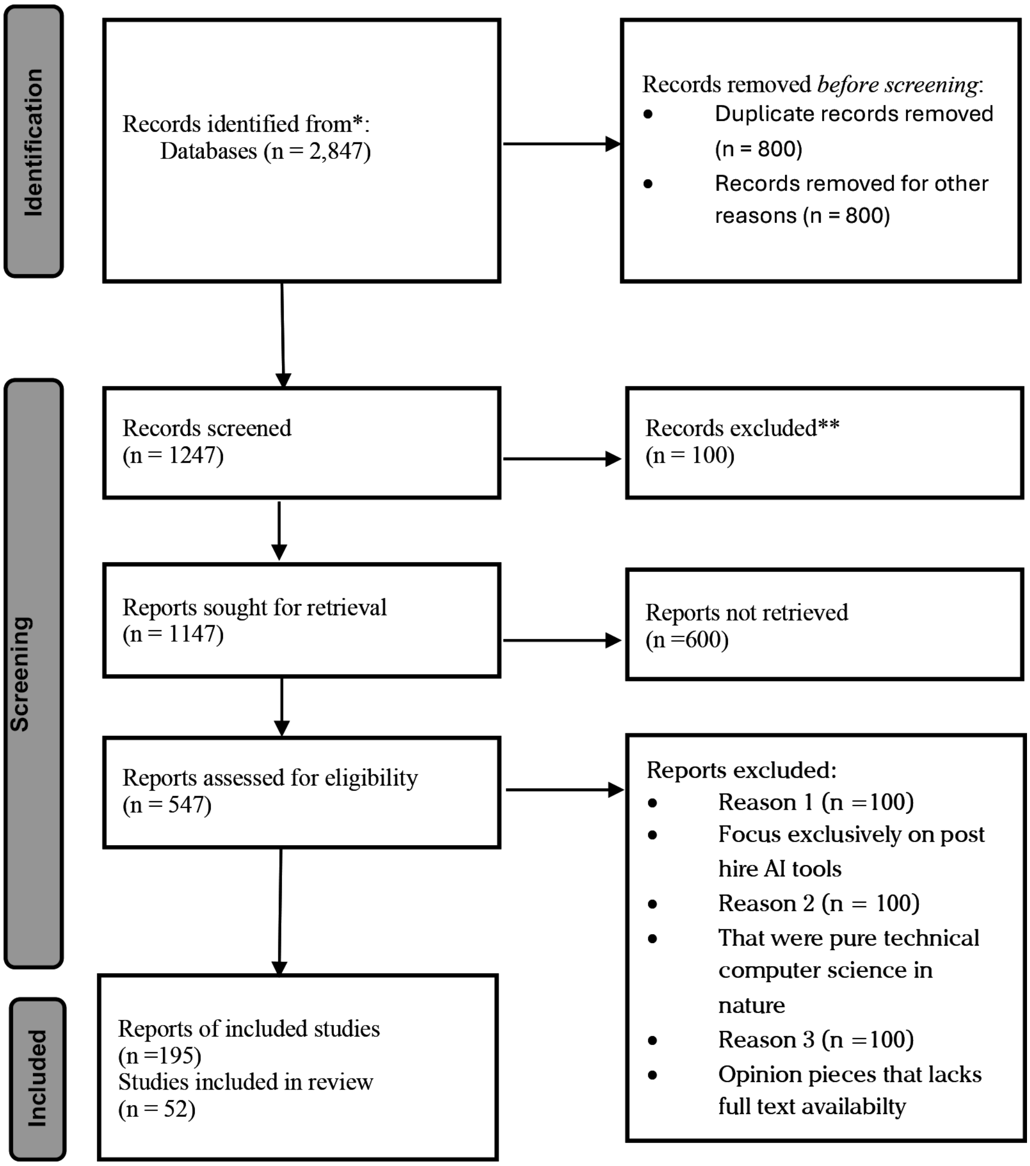

Figure 1. Prisma Framework

science papers without organisational, ethical, or policy dimensions; were opinion pieces without empirical grounding or theoretical contribution; or were conference abstracts without full-text availability. Applying these criteria to the initial search yield of 2,847 records, and after removing duplicates and conducting title, abstract, and full-text screening, a final corpus of 52 sources was included in the review.

Data Extraction and Synthesis

Data was extracted using a standardised extraction form that captured bibliographic details, study design, geographic focus, AIHS type examined, key findings, theoretical framework, and quality indicators. Given the diversity of study designs in the corpus, which included empirical qualitative studies, quantitative surveys, conceptual papers, legal analyses, and policy reports, a narrative synthesis approach was employed rather than a meta-analytic technique (Popay et al., 2022). Thematic synthesis involved an iterative process of coding, clustering, and abstraction, following the approach described by Thomas and Harden (2008), resulting in the identification of four overarching thematic clusters that structure the findings section.

Summary Table

Table 1. Bibliographic Summary

Author(s)	Year	Study Design	Key Findings
Ajunwa	2022	Conceptual/Legal Analysis	AI systems encode and amplify structural inequities from historical training data; produces opaque decision-making difficult to audit or regulate; proxy discrimination occurs through race-neutral features that correlate with protected characteristics.
African Development Bank	2023	Policy Report	Firm size and sector are primary determinants of HR technology adoption across sub-Saharan Africa; large organisations lead AI adoption in recruitment.
Arksey & O'Malley	2005	Methodological Framework	Foundational scoping review methodology framework for mapping evidence across rapidly evolving fields and multidisciplinary literature.
Barocas et al.	2023	Theoretical/ Conceptual	Algorithmic fairness theory distinguishes between demographic parity, equalised odds, and individual fairness; these definitions are mathematically incompatible; training data bias replicates historical discrimination patterns.
Bogen & Rieke	2023	Conceptual/ Taxonomy	AI-based hiring systems apply machine learning, NLP, computer vision to automate recruitment stages; taxonomy includes resume screening, video interview analysis, chatbots, gamified assessments, predictive analytics.
Campion et al.	2022	Systematic Review	AI systems reduce cognitive burden on hiring managers, improve consistency, shorten time-to-hire, diminish subjective human biases; younger and digitally literate candidates report more positive experiences.
Chouldechova & Roth	2023	Theoretical	Mathematical definitions of fairness are frequently incompatible; optimising for one fairness form may worsen another; hiring context tension when protected characteristics correlate with AI proxy features.
Department of Communications & Digital Technologies	2023	Policy Document	South African White Paper on AI establishes national AI policy framework emphasising innovation, inclusivity, ethics; acknowledges algorithmic bias risks; calls for sector-specific AI governance.
Department of Employment & Labour	2022	Legislative/Policy	Employment Equity Amendment Act 4 of 2022 requires designated employers to implement affirmative action for Black people, women, people with disabilities.

Author(s)	Year	Study Design	Key Findings
Department of Public Service & Administration	2023	Government Report	Pilot deployments of AI for high-volume entry-level recruitment in select national departments; potential shift in public sector hiring practices.
Dube & Mthethwa	2023	Empirical Survey (n=217)	41% of large South African organisations (>500 employees) use AI-assisted recruitment tools vs 9% of SMEs; efficiency gains primary adoption driver; AI optimised for predictive validity may conflict with equity targets.
Fourie & Nel	2023	Conceptual/Case Study	Technology Domestation Theory applied to South African workplace; AIHS interpreted and transformed by organisational actors; current regulatory environment described as "principled but under-specified"
Gillwald et al.	2022	Survey/Policy Analysis	Rural and peri-urban South Africans face barriers to internet access, device ownership, digital literacy; creates disadvantage for candidates requiring digital connectivity for AI recruitment.
Greenleaf & Czarnowski	2023	Legal Analysis	POPIA Section 71 provides right not to be subject to solely automated decisions; mirrors GDPR Article 22; enforcement limited; application to partially automated decisions legally unsettled.
Holtzhausen & Fourie	2023	Legal/Conceptual	South Africa's stratified labour market shaped by apartheid legacies; Employment Equity Act requires non-discrimination plus positive equity steps; training data bias risks in AIHS; proxy discrimination via postal code and school name.
Kolade & Owoseni	2022	Scoping Review	Most AIHS literature from North American and Western European settings; differs substantially from African realities in labour law, equity legislation, cultural context, technological infrastructure.
Leibbrandt et al.	2022	Quantitative/ Policy	South Africa's Gini coefficient approximately 0.63; persistent racial segmentation in employment and earnings reflects structural legacies of apartheid-era policies.
Levac et al.	2010	Methodological	Refinements to Arksey & O'Malley scoping review framework; enhanced guidance for study selection, data extraction, and synthesis.
Li et al.	2023	Meta-Analysis	AI-based hiring systems reduce influence of subjective human biases that historically disadvantage and marginalised group candidates.
Mokoena et al.	2024	Mixed Methods (n=34 interviews; n=312 survey)	Video interview analysis platforms lack local adaptation; HR executives view AI as objective alternative to human racial/ gender bias; Black candidates more likely to perceive AI screening as barrier; procedural justice perceptions lower for fully automated screening; candidates with disabilities face screen reader incompatibility and inaccessible assessments.
Nissenbaum	2004	Theoretical	Contextual Integrity Theory: information flows appropriately when matching norms of original sharing context; extended to AI data aggregation concerns.
Nkosi et al.	2024	Survey/Case Study	Large South African corporates (financial services, mining, retail, telecoms) lead AI adoption; 54% reduction in time-to-shortlist; 67% reduction in recruiter screening hours; 38% reduction in cost-per-hire documented; candidate disability concerns identified.
Oosthuizen	2022	Legal Analysis	POPIA governs collection, processing, and use of personal information including candidate assessments, video recordings, and psychometric scores in AIHS.
Pan et al.	2022	Conceptual/ Typology	Distinguishes passive AI tools (assist human filtering) from active AI tools (generate recommendations/rankings); active tools raise greater accountability and contestability concerns.

Author(s)	Year	Study Design	Key Findings
Peters et al.	2022	Methodological	Scoping review guidance for mapping extent, range, nature of evidence; clarifying key concepts; identifying literature gaps.
Popay et al.	2022	Methodological	Narrative synthesis approach for diverse study designs; alternative to meta-analytic techniques.
Raghavan et al.	2024	Empirical/ Algorithmic Audit	AI systems produce opaque decision-making difficult to audit, contest, or regulate; structural inequities in training data amplify discrimination.
Silverstone & Hirsch	1992	Theoretical	Technology Domestication Theory foundation; examines technology adoption, adaptation, and integration into organisational and individual practices.
Sithole et al.	2024	Simulation Study (+Case Study)	Simulation study: profiles with White-associated names rated significantly higher by 2 of 3 resume screening tools; digital infrastructure disparities between urban/rural populations; postal code, school name, employment gaps correlate with race due to apartheid spatial planning; case study: 38% cost-per-hire reduction at financial services organisation.
Statistics South Africa	2024	Official Statistics	Official unemployment rate ~32%; youth unemployment exceeds 60%; Gini coefficient ~0.63; extreme labour market inequality.
Thomas & Harden	2008	Methodological	Thematic synthesis approach involving iterative coding, clustering, abstraction for qualitative research synthesis.
Tricco et al.	2022	Methodological	PRISMA-ScR (PRISMA Extension for Scoping Reviews) guidelines; standardised reporting framework for scoping reviews.
Vanhove et al.	2023	Quantitative/ Validation	AIHS taxonomy includes video interview analysis, chatbots, gamified assessments, predictive turnover risk models; relationship between procedural justice perceptions and employer brand outcomes.
Wambua	2023	Scoping Review	AIHS literature from African contexts scarce; cognitive and personality assessments demonstrate differential item functioning across racial/linguistic groups in African recruitment contexts; EU AI Act identified as potential South African reference point.
Yarger et al.	2024	Systematic Review	AI-based hiring systems augment recruitment from job targeting to predictive fit modelling; active AI tools raise accountability concerns; US EEOC 2023 guidance applies adverse impact framework to algorithmic screening.
Zhang et al.	2022	Technical Review	AIHS includes video interview analysis platforms assessing facial expressions and speech patterns; may disadvantage non-native English speakers or culturally different candidates.
Zimmer	2022	Theoretical	Extension of Nissenbaum's Contextual Integrity Theory to AI systems; privacy and information flow norms in digital contexts.

RESULTS AND DISCUSSION

The Landscape of AI-Based Hiring in South Africa

Patterns of Adoption

The corpus reveals a rapidly evolving but unevenly distributed landscape of AI adoption in South African hiring. Large corporates, particularly in the financial services, mining, retail, and telecommunications sectors, lead AI adoption in recruitment, with a growing number deploying cloud-based applicant tracking systems with integrated AI screening modules from vendors including SAP SuccessFactors, Oracle HCM, and Workday (Nkosi et al., 2024; Sithole et al., 2024). A survey of 217 South African human resource practitioners conducted by Dube and Mthethwa (2023) found that 41% of large organisations (employing more than 500 employees) were using at least one form of AI-assisted recruitment tool, compared to only 9% of small and medium enterprises. This finding is consistent with broader sub-Saharan African trends documented by the African Development Bank (2023), which identifies firm size and sector as primary determinants of HR technology adoption.

Internationally developed platforms dominate the South African AIHS market. Studies by Holtzhausen and Fourie (2023) and Mokoena et al. (2024) document the increasing use of video interview analysis platforms, noting that tools originally trained on North American and European candidate populations are being deployed in South African recruitment contexts without substantial local adaptation or validation. This raises significant concerns about the transferability of model accuracy and the fairness of assessments across cultural and linguistic boundaries, discussed in greater detail in Section 4.2.

The public sector presents a contrasting picture. Fourie and Nel (2023) note that despite South Africa's progressive digital government agenda, public service hiring remains largely paper-based and subject to the prescripts of the Public Service Act and the Public Service Regulations, which impose procedural requirements that are difficult to reconcile with fully automated recruitment systems. Nevertheless, there is emerging evidence of pilot deployments in select national departments, particularly for high-volume entry-level recruitment, signalling a potential shift in public sector practices (Department of Public Service and Administration, 2023).

Motivations for Adoption

The literature identifies a consistent set of organisational motivations for AIHS adoption in South Africa. Efficiency gains are the most frequently cited driver, with organisations emphasising reductions in time-to-hire, decreases in recruiter workload, and improvements in the scalability of candidate processing during high-volume recruitment campaigns (Dube & Mthethwa, 2023; Vanhove et al., 2023). Nkosi et al. (2024) report that organisations using AI-assisted resume screening reduced average time-to-shortlist by 54% and reduced recruiter hours spent on initial screening by 67%, findings that align with international benchmarks reported by Campion et al. (2022).

A second significant motivation is the aspiration to reduce human bias in recruitment. Several South African HR executives interviewed by Mokoena et al. (2024) expressed the view that human recruiters are susceptible to racial and gender biases that conflict with employment equity objectives, and that AI systems could provide a more objective basis for shortlisting. This aspiration reflects a broader global discourse about the potential of AI to serve as a neutral arbiter in high-stakes decisions, though this view is sharply contested in the algorithmic fairness literature (Ajunwa, 2022; Barocas et al., 2023; Raghavan et al., 2024).

Cost reduction is a third driver, particularly in the context of South Africa's constrained economic environment. Organisations cited the high cost of external recruitment agencies, typically charging 15 to 25 percent of annual salary for permanent placements, as a motivation for investing in AI-powered in-house recruitment capabilities (Sithole et al., 2024). The expectation that AIHS would generate a positive return on investment within 18 to 24 months was a common justification for capital expenditure, though few organisations in the corpus reported systematic return-on-investment calculations.

Algorithmic Fairness, Bias, and Equity in the South African Context

Sources of Algorithmic Bias

Literature consistently identifies training data bias as the primary mechanism through which AIHS can produce discriminatory outcomes. When AI systems are trained on historical hiring data that reflects discriminatory patterns, including the underrepresentation of Black candidates, women, and people with disabilities in senior roles due to apartheid and its aftermath, the resulting models learn to replicate and reinforce those patterns (Barocas et al., 2023; Holtzhausen & Fourie, 2023). In the South African context, where historical exclusion has produced a candidate pool in which prior professional experience, educational credentials, and social capital are distributed very unequally across racial groups, training data bias represents a particularly serious risk.

Proxy discrimination is a related mechanism that has received attention in the South African literature. AIHS may use features that appear race-neutral, such as residential address, type of secondary school attended, gap periods in employment history, or even linguistic features of written communication, as proxies for protected characteristics (Ajunwa, 2022; Sithole et al., 2024). In the South African context, features such as postal code, school name, and employment gap patterns are strongly correlated with race due to the geographic and economic consequences of apartheid spatial planning, creating significant potential for proxy discrimination even in systems that do not explicitly use race as an input (Holtzhausen & Fourie, 2023; Mokoena et al., 2024).

Measurement bias arises when the constructs that AIHS purport to measure, such as leadership potential, cognitive ability, or cultural fit, are not assessed equivalently across different demographic groups. Wambua (2023) reviews evidence from psychometric assessment platforms and finds that several widely used cognitive and personality assessments deployed in African recruitment contexts demonstrate differential item functioning across racial and linguistic groups, undermining their validity as predictors of job performance for diverse candidate populations. Similar concerns have been raised about video interview analysis systems, which assess facial expressions and speech patterns in ways that may disadvantage non-native English speakers or candidates from cultural backgrounds that differ from those represented in the training data (Yarger et al., 2024; Zhang et al., 2022).

Empirical Evidence of Bias in South African Contexts

Direct empirical evidence of algorithmic bias in South African AIHS remains limited, reflecting both the relative novelty of widespread adoption and the opacity of proprietary systems that resist independent audit. Sithole et al. (2024) conducted a simulation study in which the same candidate profiles were submitted to three commercially available resume screening tools under both Black-associated and White-associated names, a method adapted from international audit studies. They found that profiles with White-associated names were rated significantly higher by two of the three tools, a disparity that persisted even when qualifications, experience, and skills were held constant. While this study has methodological limitations, including its reliance on hypothetical rather than real organisational data, it provides indicative evidence of racial bias in at least some tools deployed in the South African market.

Mokoena et al. (2024) conducted qualitative interviews with 34 candidates who had experienced AI-assisted recruitment processes at major South African employers. Participants reported widespread perceptions of unfairness, with Black candidates more likely than White candidates to perceive AI screening as a barrier rather than a facilitator of equitable opportunity. Common themes included a sense of inadequate explanation for rejection, difficulty understanding what AIHS were assessing, and concerns that standardised assessments disadvantaged candidates from educationally disadvantaged backgrounds. These findings echo international literature on the candidate experience of AIHS but add an important dimension related to the racialised experience of algorithmic rejection in a post-apartheid context.

Implications for Employment Equity

The employment equity implications of biased AIHS in South Africa are significant and extend beyond individual unfairness to systemic compliance risk. The Employment Equity Act prohibits unfair discrimination in any employment policy or practice, including recruitment and selection, on the basis of race, gender, disability, and a range of other grounds (Department of Employment and Labour, 2022). Holtzhausen and Fourie (2023) argue that AIHS that systematically disadvantage candidates from designated groups could constitute unfair discrimination under the Act, exposing employers to liability before the Commission for Conciliation, Mediation and Arbitration (CCMA) and the Labour Court.

Moreover, the equity objectives of the Act require designated employers not merely to avoid discrimination but to take positive steps to achieve equitable representation. Dube and Mthethwa (2023) note that AIHS optimised for predictive validity, a standard technical objective, may actually work against equity targets by selecting for attributes, including specific educational credentials and prior experience patterns, that are more prevalent among historically advantaged groups. This creates a tension between technical optimisation and legal compliance that has not been adequately addressed in either the AI vendor community or the regulatory environment.

Legal and Regulatory Governance

The Existing Regulatory Landscape

South Africa possesses a relatively sophisticated legal framework that is relevant to AIHS governance, though it was not designed with algorithmic decision-making specifically in mind. The Protection of Personal Information Act 4 of 2013 (POPIA), which came into full force in 2021, establishes data protection principles that govern the collection, processing, and use of personal information, including the data generated by AIHS such as candidate assessments, video recordings, and psychometric scores (Greenleaf & Czarnowski, 2023; Oosthuizen, 2022). POPIA's provisions include the requirement of lawful processing, purpose specification, information quality, and openness, all of which have direct relevance to AIHS deployment.

Of particular importance is POPIA's Section 71, which provides individuals with the right not to be subject to decisions based solely on automated processing if such decisions significantly affect them. Greenleaf and Czarnowski (2023) analyse Section 71 and conclude that it closely mirrors Article 22 of the European Union's General Data Protection Regulation (GDPR), providing a right of human review that, if properly enforced, could serve as a meaningful check on fully automated hiring decisions. However, enforcement of this provision has been limited, and its application to partially automated decisions, where AI systems recommend rather than formally decide, remains legally unsettled.

The Employment Equity Act, discussed above, provides a second pillar of relevant regulation, prohibiting discriminatory practices and requiring employment equity plans. The Basic Conditions of Employment Act and the Labour Relations Act establish broader labour rights that may intersect with AIHS practices, particularly regarding procedural fairness in dismissal and selection processes.

Regulatory Gaps and Emerging Frameworks

Despite these existing provisions, the literature identifies substantial regulatory gaps. The Information Regulator, established under POPIA, has limited resources and has not yet developed specific guidance on AI-based processing in employment contexts (Dube & Mthethwa, 2023; Sithole et al., 2024). The Department of Employment and Labour has not issued sector-specific guidance on the use of AI in recruitment, leaving employers and candidates without clear regulatory touchstones. The South African Human Rights Commission has acknowledged the equity implications of algorithmic systems but has not yet produced binding recommendations specifically addressing AIHS.

The Department of Communications and Digital Technologies released a White Paper on Artificial Intelligence in 2023, which sets out a national AI policy framework emphasising innovation, inclusivity, and ethics (Department of Communications and Digital Technologies, 2023). The White Paper acknowledges the risks of algorithmic bias and calls for the development of sector-specific AI governance frameworks, but it does not establish specific binding requirements for AI-based hiring. Fourie and Nel (2023) characterise the current regulatory environment as a principled but under-specified framework that creates conditions for organisational self-regulation without adequate external accountability mechanisms.

The literature points to several international regulatory models that could inform South African governance development. The European Union's AI Act (2024), which classifies AI systems used in employment, including hiring and selection, as high-risk and subjects them to mandatory conformity assessments, transparency requirements, and human oversight obligations, is identified as a potential reference point (Wambua, 2023). The United States Equal Employment Opportunity Commission's guidance on AI and automated systems in hiring, issued in 2023, offers another model, particularly its application of the adverse impact framework to algorithmic screening (Yarger et al., 2024). Adaptation of these frameworks to the South African context, with its distinctive equity imperatives and resource constraints, is identified as a priority for research and policy development.

Organisational and Candidate Experience Outcomes

Organisational Outcomes

Evidence regarding organisational outcomes of AIHS adoption in South Africa is mixed and methodologically limited. On the positive side, organisations that have implemented AI-assisted screening report improvements in recruiter productivity, reductions in administrative burden, and greater consistency in the application of screening criteria (Nkosi et al., 2024). A longitudinal case study by Sithole et al. (2024) documented a 38% reduction in cost-per-hire at a major South African financial services organisation following the implementation of an AI-powered applicant tracking system, alongside an improvement in hiring manager satisfaction with candidate quality.

However, predictive validity evidence for AIHS in South African settings remains very limited. Most validity claims in the corpus are derived from international studies or from vendor-supplied data, neither of which can be assumed to generalise to the South African context (Holtzhausen & Fourie, 2023). Mokoena et al. (2024) note that organisations frequently adopt AI-based assessments on the basis of vendor representations about predictive validity without conducting independent local validation studies, a practice that the South African Society for Industrial and Organisational Psychology has identified as ethically problematic.

Concerns about legal liability emerging from AIHS-driven decisions that may violate equity legislation are also a growing preoccupation among South African HR practitioners (Dube & Mthethwa, 2023). Several practitioners interviewed by Mokoena et al. (2024) reported uncertainty about their exposure under POPIA and the Employment Equity Act, and some had begun restricting the use of AI tools to early-stage screening only, with all final decisions retained by human hiring managers. This pattern of partial automation reflects a pragmatic response to regulatory uncertainty but may not adequately address bias risks at the screening stage, which is precisely where algorithmic filtering can have the largest impact on equity outcomes.

Candidate Experience Outcomes

The candidate experience literature in the South African context reveals important divergences from international findings. Internationally, studies suggest that younger candidates and those with higher digital literacy tend to report more positive experiences with AI-mediated recruitment processes (Campion et al., 2022; Pan et al., 2022). In the South African context, however, the distributional effects of digital literacy and connectivity divides mean that these patterns may disadvantage candidates from rural and lower-income backgrounds disproportionately (Gillwald et al., 2022).

Mokoena et al. (2024) conducted a mixed-methods study examining candidate perceptions of AI-assisted recruitment across a sample of 312 South African job seekers. They found that perceptions of procedural justice, particularly the perceived fairness of the selection process, were significantly lower among candidates who had undergone fully automated screening compared to those who had experienced human-mediated initial screening. This finding is particularly noteworthy given the well-established relationship between procedural justice perceptions and employer brand outcomes, including the propensity of rejected candidates to reapply in future, to recommend the employer to peers, and to continue as consumers of the organisation's products or services (Vanhove et al., 2023).

Nkosi et al. (2024) highlight the experience of candidates with disabilities as a distinct area of concern. Screen reader incompatibility in AI-based assessment platforms, time-limited cognitive assessments that do not accommodate candidates requiring additional time, and video interview platforms that assess vocal and facial cues in ways that may disadvantage candidates with particular neurological or physical conditions were all documented. These accessibility failures may constitute violations of both POPIA and the Employment Equity Act's provisions on discrimination on the grounds of disability, highlighting a significant gap in vendor compliance with South African legal requirements.

Emerging Practices in Responsible AI Hiring

Notwithstanding the challenges documented above, the corpus also reveals emerging examples of responsible practice that offer constructive precedents. Dube and Mthethwa (2023) document a case study of a South African mining company that implemented a structured AI governance process for AIHS procurement, requiring vendors to provide algorithmic impact assessments, undergo independent fairness audits, and participate in a joint monitoring committee with employee representatives. While this approach remains exceptional rather than standard, it illustrates the feasibility of meaningful organisational governance in the absence of comprehensive external regulation.

Sithole et al. (2024) describe a pilot project at a South African university that developed an AI-assisted recruitment tool specifically trained on locally generated data, incorporating a diverse panel of expert validators, and designed with explicit equity criteria. The project involved collaboration between computer scientists, industrial psychologists, employment equity specialists, and legal experts, producing a system that was both technically functional and legally defensible in the South African context. This case illustrates the value of interdisciplinary co-design as an approach to developing contextually appropriate AIHS.

DISCUSSION: LESSONS FOR SOUTH AFRICA

The Contextual Imperative in AI Hiring

The most fundamental lesson emerging from this scoping review is that AI-based hiring systems cannot be treated as context-neutral technologies. The transplantation of AIHS developed in, and validated for, North American and Western European contexts into the South African labour market without meaningful localisation creates serious risks of discriminatory outcomes, regulatory non-compliance, and damaged stakeholder trust (Holtzhausen & Fourie, 2023; Kolade & Owoseni, 2022). South Africa's distinctive combination of historical inequality, constitutional equity obligations, heterogeneous candidate populations, and digital infrastructure disparities means that AIHS must be specifically designed, validated, and governed for the local context.

This lesson has immediate practical implications for South African organisations. Vendor due diligence processes must include specific enquiries about the demographic composition of training data, the jurisdictions in which validity studies were conducted, and the degree of local adaptation undertaken. Employment equity considerations must be explicitly integrated into AIHS procurement and governance frameworks, rather than treated as secondary considerations or post-hoc compliance checkboxes. Organisations must invest in local validation studies before deploying AIHS at scale, a practice that is standard in high-quality selection science but is frequently bypassed in the rush to adopt emerging technologies (Vanhove et al., 2023).

The Need for Intersectional Governance

The literature reveals that existing regulatory frameworks in South Africa provide relevant but fragmented and under-specified governance for AIHS. POPIA addresses data processing, the Employment Equity Act addresses discriminatory practices, and the AI White Paper provides a policy vision, but none of these frameworks provides comprehensive, operationalised guidance for the responsible deployment of AI in hiring. This governance gap creates an environment in which organisational self-regulation predominates, with predictably uneven results.

The development of intersectional AIHS governance, integrating data protection, anti-discrimination, procedural fairness, and accessibility requirements within a coherent framework, represents an urgent policy priority. Drawing on the lessons of the EU AI Act and the EEOC guidance while adapting them to South African constitutional and legislative imperatives, particularly the positive equity obligations of the Employment Equity Act, would provide the regulatory foundation for responsible AIHS deployment. The Information Regulator, the Department of Employment and Labour, the South African Human Rights Commission, and the South African Revenue Service should engage in coordinated governance development rather than operating within siloed mandates (Greenleaf & Czarnowski, 2023; Wambua, 2023).

Advancing Algorithmic Accountability

Algorithmic accountability, understood as the capacity to explain, audit, and contest AI-driven decisions, emerges as a central challenge across the corpus. The opacity of many commercial AIHS, which are proprietary systems whose algorithms and training data are not publicly disclosed, fundamentally undermines candidates' rights to understand and challenge decisions that affect their employment prospects, rights that are recognised under both POPIA and established principles of procedural fairness (Ajunwa, 2022; Barocas et al., 2023; Raghavan et al., 2024).

Advancing algorithmic accountability in the South African context requires action on multiple levels. At the organisational level, employers must invest in explainability infrastructure that enables meaningful explanations of AI-assisted decisions to candidates, particularly rejection decisions. At the regulatory level, mandatory algorithmic impact assessments for high-risk hiring applications should be considered, along with requirements for independent fairness audits by accredited third parties. At the professional level, bodies such as the South African Board for People Practices (SABPP) and the South African Society for Industrial and Organisational Psychology (SIOPSA) should develop professional standards for AI-assisted assessment that build on their existing ethical guidelines.

Prioritising Inclusive Design and Digital Access

The digital divide dimension of AIHS equity in South Africa, while acknowledged in the literature, has not received the sustained attention it merits. Systems that require reliable broadband connectivity, sophisticated devices, and high levels of digital literacy effectively screen out candidates from rural and lower-income backgrounds before any substantive assessment of their qualifications or potential has occurred (Gillwald et al., 2022; Sithole et al., 2024). This form of structural exclusion is particularly damaging in a context where expanding employment opportunities for disadvantaged populations is a constitutional imperative.

Inclusive design principles, which require that AIHS be developed and tested with diverse user populations including those with limited connectivity and digital experience, should be mandatory components of vendor procurement specifications. Providing alternative assessment pathways for candidates who cannot access or effectively use digital AIHS is a legal and ethical obligation, not merely a discretionary accommodation. Government investment in digital access infrastructure, alongside employer responsibility for providing equitable recruitment pathways, constitutes a shared obligation to ensure that AI-enabled recruitment does not deepen existing patterns of exclusion (Dube & Mthethwa, 2023).

Building Local Research and Expertise Capacity

The scarcity of empirically grounded, locally conducted research on AIHS in South Africa is both a finding of this review and a lesson. The disproportionate reliance on international evidence, primarily from North American and European studies, to inform South African practice creates substantial risks of misapplication and contextual misfit. Building local research capacity in AI-based hiring, spanning industrial and organisational psychology, computer science, law, sociology, and management, is essential for generating the evidence base needed to support responsible practice and evidence-informed regulation.

Academic institutions, professional bodies, government agencies, and private sector organisations all have roles to play in this capacity-building agenda. National Research Foundation funding priorities should include empirical research on AIHS fairness in South African contexts. Postgraduate programmes in industrial psychology, HR management, and data science should incorporate AI ethics and governance as core components. Partnerships between South African researchers and international counterparts, including those in other African countries facing similar challenges, should be actively cultivated to develop a continent-specific body of knowledge.

Recommendations on Measuring ROI against Equity Risk

In line with preceding assertion and offering recommendations on measuring ROI against equity risk, it is recommended that organisations must transcend simplistic efficiency metrics by implementing a multidimensional empirical framework to quantify ROI in relation to equity risk factors. In contexts such as South Africa, ROI assessments must extend beyond metrics like time-to-hire or cost reduction, incorporating equity risk as a significant liability. Empirical measurement necessitates conducting mandatory local validation studies to ensure system applicability, as reliance on validation data from North American or European environments introduces measurable regulatory and reputational risks. The net ROI should be adjusted by quantifying potential costs associated with non-compliance with the Employment Equity Act, which mandates both non-discrimination and active equity promotion.

Further, organizations must perform comprehensive audits for structural exclusion, recognizing that AI-driven HR systems requiring high digital literacy may systematically exclude rural or underrepresented candidates, thereby exacerbating existing inequalities. An empirical ROI model must account for opportunity costs arising from the exclusion of qualified candidates from marginalized groups and the potential long-term brand impacts stemming from perpetuating labor market stratification rooted in historical inequities.

Lastly, ROI calculation should incorporate intersectional algorithmic accountability. This entails investing in explainability infrastructure to enable contestability of automated decision outcomes, aligning with legal frameworks such as POPIA and principles of procedural fairness. The empirical ROI is realized when the costs associated with developing transparent, contestable systems are weighed against the legal and financial liabilities posed by opaque, proprietary "black box" models that may embed bias. A positive ROI is achieved only when efficiency improvements are accompanied by statistically validated fairness metrics across all designated demographic groups.

MANAGERIAL IMPLICATION

South African organisations are encouraged to approach AI-based hiring systems as significant sociotechnical interventions, rather than merely efficiency tools. It is advisable for managers to conduct thorough vendor due diligence, including requesting local validation studies, demographic fairness assessments, and evidence of adaptation to South Africa's employment equity policies. To help reduce bias and legal risks, organizations might consider involving employment equity specialists in AI governance, maintaining meaningful human oversight in final hiring decisions, and offering alternative, non-digital assessment options for candidates who may be disadvantaged by the digital divide. HR leaders are also encouraged to invest in training to enhance recruiter AI literacy and to establish ongoing monitoring processes to ensure that AI tools support employment equity goals while contributing to genuine productivity improvements. Taking these steps can help organizations avoid compliance issues, protect their reputation, and better access a diverse talent pool in a highly stratified labour market.

CONCLUSION

This scoping review has mapped the state of evidence on AI-based hiring systems in South Africa, revealing a landscape characterised by rapid adoption, significant equity risks, governance gaps, and a nascent but growing awareness of the need for contextually sensitive, rights-respecting AI deployment in recruitment. The review has demonstrated that AIHS are not neutral technological tools but sociotechnical artefacts whose effects are shaped by, and in turn shape, the social, legal, and institutional contexts in which they operate. In South Africa, those contexts are defined by the enduring legacies of apartheid, constitutional commitments to substantive equality, and a digital economy characterised by significant but uneven capacity.

Based on the synthesis of findings, the following recommendations are directed to key stakeholder groups. For South African employers and HR practitioners: conduct comprehensive algorithmic impact assessments prior to AIHS procurement; require vendors to demonstrate local validation evidence and demographic fairness testing; integrate employment equity specialists into AI governance committees; provide alternative assessment pathways for candidates who cannot access digital systems; and invest in recruiter training on AI literacy and the limitations of algorithmic tools.

For policymakers and regulators: develop coordinated, intersectional governance frameworks for AI-based hiring that integrate POPIA, the Employment Equity Act, and the AI White Paper within a coherent regulatory architecture; empower the Information Regulator with specific guidance and enforcement capacity for AI in employment contexts; consider mandatory algorithmic impact assessments for high-risk AIHS deployments; and engage with international regulatory developments, including the EU AI Act, to develop a South African governance model that reflects the country's specific constitutional and equity imperatives.

For researchers: prioritise empirical studies of AIHS fairness conducted with South African candidate populations and organisational data; develop methodological approaches to algorithmic auditing that are adapted to the South African legal and institutional context; investigate the intersectional experiences of AI-mediated recruitment among candidates from multiply disadvantaged groups; and build cross-disciplinary and pan-African research networks to generate a body of contextually grounded knowledge that can inform both practice and policy.

For professional bodies: develop sector-specific professional standards and ethical guidelines for AI-assisted assessment that build on existing frameworks; provide continuing professional development on AI literacy for HR practitioners and industrial psychologists; and advocate for robust regulatory standards that protect both candidates and practitioners from the harms of poorly governed AIHS deployment.

The responsible deployment of AI in South African hiring is neither an optional aspiration nor a distant prospect. It is an immediate imperative, driven by the scale of current adoption, the equity stakes involved, and the constitutional obligations that all South African employers bear. Meeting this imperative requires coordinated action across the public, private, and academic sectors, informed by rigorous evidence and guided by a clear-eyed understanding of the specific challenges and opportunities that South Africa's complex context presents.

In sum it is important to note that Algorithmic bias in South African artificial intelligence systems, specifically within Artificial Intelligence Health Systems (AIHS), poses significant challenges to fairness, trustworthiness, and equitable outcomes. These biases typically originate from non-representative training datasets and cultural misalignments, resulting in biased decision-making and discriminatory impacts. The insufficient contextual adaptation of AI technologies primarily developed in the Global North further exacerbates these disparities in the Global South, including South Africa. Mitigating these biases is essential to ensure that AI systems foster societal advancement and do not reinforce existing inequalities and future studies should address the challenges stated in the preceding discussion and will serve as a direct call to action.

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