AI and Workforce Diversity: A Structural Model for Inclusive Hiring in the Digital Age

Nitish Kumar Minz[1] and Manish Kumar[2] and Monika Yadav*[3] , Chandra Mohan[4]

[1]VIT Business School, Vellore Institute of Technology, Vellore, Tamil Nadu, India

[2]L N Mishra College of Business Management, Muzaffarpur, Bihar, India

[3]School of Management & Commerce, K.R. Mangalam University, Gurugram 122103, India

[4]School of Basic & Applied Sciences, K R Mangalam University, Gurugram 122103, India

*Corresponding author email: monikayadav5008@gmail.com; gurgaonmohan@yahoo.co.in

Abstract

This research investigates the transformative role of Artificial Intelligence (AI) in Human Resource Management (HRM), particularly in fostering inclusive hiring by reducing unconscious bias. It introduces two novel constructs—AI Bias Awareness and Inclusion Technology Readiness—to examine how psychological and technological factors influence the intention to adopt AI for diversity-focused recruitment. Data was collected from 402 HR professionals in AI-adopting Indian firms using purposive sampling and a structured online questionnaire. Covariance-based Structural Equation Modeling (CB-SEM) with AMOS v25 was employed to test direct, mediated, and moderated relationships among key constructs. Results indicate that perceived algorithmic fairness and recruiter trust significantly affect inclusive hiring intentions. AI bias awareness enhances fairness perceptions, which subsequently build trust. Inclusion readiness further moderates this relationship. The study contributes a validated, multi-dimensional model of inclusive AI adoption in HRM and offers actionable insights for aligning AI hiring systems with Diversity, Equity, and Inclusion (DEI) goals.

Keywords: Inclusive Hiring, Workforce Diversity, Algorithmic Fairness, Recruiter Trust, AI Bias Awareness, Structural Equation Modeling.

1. Introduction

Artificial Intelligence (AI) has rapidly transformed the landscape of Human Resource Management (HRM), offering unprecedented opportunities for efficiency, objectivity, and strategic alignment in decision-making processes. Among the most notable transformations lies

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the integration of AI in hiring and talent acquisition, where intelligent algorithms are used to screen resumes, rank candidates, conduct video interviews, and even predict job performance (Abraham, 2025; Tambe et al., 2019). In parallel with these advancements, organizations worldwide are increasingly placing emphasis on workforce diversity and inclusive hiring as critical drivers of innovation, reputation, and long-term business sustainability (Ozkazanc-Pan, 2021; Søraa, 2022). However, the intersection of AI and inclusion remains an under-explored and contested domain—where technological promises must confront ethical dilemmas and deeply rooted biases.

Inclusive hiring, broadly defined as the design and execution of recruitment practices that foster equity and representation across gender, caste, ethnicity, age, ability, and socioeconomic status, has evolved from being a compliance mandate to a strategic business imperative (Kelan, 2023). Firms with diverse teams are statistically more likely to outperform their peers in creativity, financial performance, and employee engagement (Sinha & Kumar, 2021; Talajić et al., 2024). However, traditional hiring systems are often susceptible to unconscious biases stemming from recruiters' cognitive limitations and cultural preconditioning (Lind, 2001; Zliobaite, 2017). AI is perceived as a potential solution to these challenges by enabling standardized assessments, anonymized candidate evaluations, and data-driven decision-making (Oman et al., 2024; Vivek, 2023). Yet, paradoxically, AI systems are also vulnerable to algorithmic bias if trained on skewed data or embedded with opaque logic (Binns, 2021; Zou & Schiebinger, 2018).

A growing body of literature has critically examined the risks and implications of using AI in recruitment. For example, Binns et al. (2018) argue that fairness in algorithmic decision-making requires a context-aware understanding of justice and bias mitigation. Rigotti and Fosch-Villaronga (2024) emphasize the importance of transparency, accountability, and human oversight in AI systems deployed for HR functions. Moreover, empirical studies have shown that organizational actors—such as HR professionals and hiring managers—are often unaware of the biases embedded in AI tools and tend to overestimate their neutrality (Raji & Buolamwini, 2019; Houser, 2019). This has significant implications for inclusive hiring, where the effectiveness of AI tools is not merely a function of their design, but also of how they are perceived, trusted, and implemented by human agents in organizational settings.

Despite these concerns, AI continues to be integrated into recruitment systems at scale, particularly in digitally evolving economies where AI-enabled HR platforms are expanding rapidly (Raj, 2024; Srivastava, 2024). Emerging employment landscapes characterized by

structural inequities, underrepresentation of women in leadership roles, and limited access for marginalized communities provide a critical context for evaluating the inclusive potential of AI-driven hiring tools (Nacheva, 2024; Stypinska, 2023). While organizations may adopt AI to standardize and streamline recruitment, the extent to which these tools are aligned with inclusion goals remains unclear.

Moreover, limited academic attention has been paid to the behavioral and perceptual factors that drive or hinder the adoption of AI for inclusive hiring. Constructs such as AI bias awareness, perceived algorithmic fairness, recruiter trust, and organizational readiness for inclusive technologies have not been holistically studied within a single model. Existing research often treats these variables in isolation, focusing either on technological design or on organizational outcomes, without bridging the gap between perception, behavior, and system effectiveness (Davis, 1989; Venkatesh et al., 2003; Grandhi & Patil, 2013).

To address this gap, the current study investigates the following research questions:

RQ1: How does AI bias awareness influence perceived algorithmic fairness and recruiter trust in AI-driven hiring tools?

RQ2: To what extent do fairness perception, recruiter trust, and organizational readiness impact the intention to adopt AI for inclusive hiring?

To answer these questions, a novel conceptual framework is proposed, drawing on the Theory of Planned Behavior (Ajzen, 1991), the Technology Acceptance Model (Davis, 1989), and contemporary perspectives on algorithmic justice and fairness in AI systems (Binns, 2021; Zliobaite, 2017). The framework incorporates five key constructs: (1) AI Bias Awareness, (2) Perceived Algorithmic Fairness, (3) Recruiter Trust in AI, (4) Inclusion Technology Readiness, and (5) Inclusive Hiring Intention. The model hypothesizes both direct and mediated relationships, where perceived fairness and trust act as mediators between awareness and intention, while inclusion readiness moderates the link between fairness and trust (see Figure 1). The inclusion of trust and fairness constructs is further grounded in prior research emphasizing the importance of technological acceptance and confidence in AI-enabled decision systems (Venkatesh et al., 2003; McKnight et al., 2002).

This study uses quantitative survey data collected from 402 HR professionals and talent acquisition specialists working in AI-integrated recruitment environments across India. The

participants were selected using a non-probability purposive sampling technique, targeting individuals with direct exposure to AI-driven hiring platforms such as resume screening tools, chatbots, or algorithmic shortlisting systems (Abraham, 2025; Raj, 2024). The sample comprised professionals from key sectors including Information Technology (IT), Banking and Financial Services (BFSI), Consulting, E-commerce, and Healthcare, thereby ensuring industry diversity and contextual relevance. The data were analyzed using covariance-based structural equation modeling (CB-SEM) through AMOS v25 to test the hypothesized relationships and validate the measurement model. The measurement validation procedures followed established guidelines for reliability, convergent validity, and discriminant validity in SEM research (Hair et al., 2019; Fornell & Larcker, 1981; Henseler et al., 2015). The findings not only offer empirical insights into the psychological and technological dynamics of AI-HRM interaction but also provide actionable recommendations for designing inclusive and bias-resistant AI systems that align with Diversity, Equity, and Inclusion (DEI) objectives (Sinha & Kumar, 2021; Søraa, 2022).

The remaining sections of this paper are organized as follows: Section 2 provides the theoretical background and hypotheses development based on prior literature; Section 3 explains the research methodology and sampling design; Section 4 presents the data analysis and SEM results; Section 5 discusses the findings, theoretical contributions, and practical implications; and Section 6 concludes with limitations and directions for future research.

2. Theoretical Background and Hypotheses Development

The rapid integration of Artificial Intelligence (AI) into organizational hiring practices presents both unprecedented opportunities and critical ethical challenges, particularly in the domain of workforce diversity and inclusion. In order to explain how AI tools can influence recruiters' intentions to adopt inclusive hiring practices, this study draws upon a confluence of theoretical frameworks—namely the Theory of Planned Behavior (TPB), Trust in Automation Theory, Justice and Fairness Theories, and the Technology Readiness Index (TRI). By grounding each construct within robust theoretical foundations, we develop a multi-pathway framework to empirically assess the factors contributing to inclusive hiring intentions in the age of algorithmic decision-making.

2.1 AI Bias Awareness and Perceived Algorithmic Fairness

AI Bias Awareness refers to an individual's recognition of the potential for AI systems to exhibit or perpetuate discriminatory behavior due to biased data, flawed model design, or lack of contextual sensitivity. This awareness has gained prominence in recent years, especially in light of documented cases where AI-based recruitment and decision systems demonstrated racial, gender, and intersectional disparities (Raji et al., 2020; Zou & Schiebinger, 2018).

Rooted in ethical and fairness-based reasoning within organizational contexts, awareness acts as the initial stage of critical evaluation in technology-mediated decision-making (Lind, 2001). From the perspective of algorithmic justice and discrimination measurement, an individual who is sensitized to the potential for bias is more likely to evaluate a system's fairness critically and with nuance (Binns, 2021; Zliobaite, 2017). When recruiters are aware of these issues but observe that the system includes built-in fairness constraints—such as transparency mechanisms, bias auditing, or explainability features—they are more likely to evaluate it as algorithmically fair and trustworthy (Raji & Buolamwini, 2019; Rigotti & Fosch-Villaronga, 2024).

H1: *AI Bias Awareness positively influences Perceived Algorithmic Fairness.*

2.2 Perceived Algorithmic Fairness and Recruiter Trust in AI

Perceived Algorithmic Fairness denotes the extent to which a recruiter believes that the AI tool in question operates without discrimination and follows equitable logic in decision-making. This aligns with procedural and distributive justice perspectives, which emphasize fairness in both decision-making processes and outcomes (Lind, 2001; Binns et al., 2018). Within the context of AI-enabled hiring, fairness is evaluated not only in terms of output equity but also in the transparency and explainability of the underlying algorithmic processes (Zliobaite, 2017; Rigotti & Fosch-Villaronga, 2024).

From a technology acceptance standpoint, the establishment of trust in AI systems hinges on perceptions of reliability, predictability, and value alignment (McKnight et al., 2002; Siau & Wang, 2018). When AI is seen as fair—treating diverse candidate profiles equitably and minimizing systemic bias—it contributes to the formation of trust by signaling ethical and organizational alignment (Raji & Buolamwini, 2019; Sinha & Kumar, 2021). Trust thus becomes a cognitive bridge through which fairness perceptions are translated into favorable

attitudes and eventual technology adoption behaviors (Venkatesh et al., 2003; Grandhi & Patil, 2013).

H2a: *Perceived Algorithmic Fairness positively influences Recruiter Trust in AI.*

2.3 AI Bias Awareness and Recruiter Trust in AI

While it may be hypothesized that awareness of AI bias leads to skepticism, contemporary perspectives on algorithmic accountability and ethical AI governance suggest a more nuanced relationship. Recruiters who are aware of potential biases do not necessarily reject AI; rather, they become more critical, reflective, and vigilant in their evaluation of such systems (Binns, 2021; Zliobaite, 2017). If they find that the AI system incorporates corrective measures—such as fairness constraints, training on diverse datasets, transparency mechanisms, or independent audits—this awareness can convert into trust due to the system's alignment with ethical and organizational justice expectations (Raji & Buolamwini, 2019; Rigotti & Fosch-Villaronga, 2024). Thus, bias-aware recruiters may exhibit greater trust in AI tools that transparently demonstrate fairness-by-design, particularly in organizational environments where diversity, equity, and inclusion are institutional priorities (Sinha & Kumar, 2021; Søraa, 2022).

H2b: *AI Bias Awareness positively influences Recruiter Trust in AI.*

2.4 Recruiter Trust in AI and Inclusive Hiring Intention

Within the framework of the Theory of Planned Behavior (TPB) (Ajzen, 1991), behavioral intention is conceptualized as a direct function of attitude. In this context, Recruiter Trust in AI serves as an attitudinal predictor influencing inclusive hiring intention. A recruiter who trusts the AI tool perceives it as reliable, fair, and effective in executing the task of equitable candidate selection. This favorable evaluation strengthens the likelihood of continued reliance on and integration of such tools within recruitment practices (Grandhi & Patil, 2013).

Technology acceptance research further supports this position by asserting that trust in intelligent systems enhances perceived usefulness and reduces uncertainty, thereby facilitating reliance and actual system usage (McKnight et al., 2002; Venkatesh et al., 2003). When AI tools are deployed in high-stakes and socially sensitive contexts—such as inclusive hiring—trust becomes particularly critical, as decision-makers must reconcile technological efficiency with ethical responsibility (Siau & Wang, 2018; Rigotti & Fosch-Villaronga, 2024). Thus, trust

emerges as a pivotal mechanism shaping the intention to incorporate AI into inclusive hiring workflows.

H3: *Recruiter Trust in AI positively influences Inclusive Hiring Intention.*

2.5 Perceived Algorithmic Fairness and Inclusive Hiring Intention

While trust mediates the effect of fairness on behavior, there is also a direct influence of Perceived Algorithmic Fairness on Inclusive Hiring Intention. According to the Theory of Planned Behavior (Ajzen, 1991), perceptions of fairness can shape behavioral intention not only through attitudinal evaluation but also by influencing subjective norms—particularly in organizational environments where diversity and inclusion are institutionalized as shared values (Venkatesh et al., 2003). When fairness is perceived to be embedded within AI systems, recruiters may feel normative reinforcement to adopt such tools in alignment with organizational expectations and ethical standards.

Furthermore, perspectives from organizational justice and algorithmic ethics suggest that fairness perceptions generate moral validation and legitimacy, which in turn promote ethically aligned behaviors (Lind, 2001; Binns et al., 2018). In the context of AI-enabled recruitment, when decision-makers perceive algorithmic processes to be procedurally and distributively fair, they are more inclined to support and implement such systems within inclusive hiring workflows (Sinha & Kumar, 2021; Rigotti & Fosch-Villaronga, 2024).

In essence, recruiters who perceive the AI tool as fair are more likely to believe that its use contributes positively to inclusion goals. This moral congruence enhances their intention to deploy such systems in future hiring cycles.

H4: *Perceived Algorithmic Fairness positively influences Inclusive Hiring Intention.*

2.6 Moderating Role of Inclusion Technology Readiness

Inclusion Technology Readiness (ITR) reflects the degree to which an organization is technologically and culturally equipped to implement AI for inclusive purposes. It is conceptually grounded in the Technology Readiness Index (TRI), which emphasizes individual and organizational predisposition toward adopting new technologies (Parasuraman, 2000), as well as broader technology adoption frameworks that highlight the importance of organizational capability and environmental alignment in innovation implementation

(Venkatesh et al., 2003; Liang & Xue, 2010). These perspectives collectively underscore that the adoption of AI-driven systems is contingent not only on perceived usefulness or fairness, but also on infrastructural preparedness, cultural compatibility, and institutional support mechanisms.

In high-readiness contexts—characterized by inclusive policies, leadership commitment, structured training programs, and fairness-centric performance indicators—the positive effect of perceived algorithmic fairness on inclusive hiring intention is amplified (Sinha & Kumar, 2021; Talajić et al., 2024). Such environments reinforce the normative and strategic value of fairness-oriented AI adoption. Conversely, in low-readiness settings where inclusion is not embedded within organizational systems or governance structures, the impact of perceived fairness may be attenuated, even if recruiters individually evaluate the AI tool as fair and ethically aligned (Ozkazanc-Pan, 2021; Søraa, 2022).

H5: *Inclusion Technology Readiness moderates the relationship between Perceived Algorithmic Fairness and Inclusive Hiring Intention.*

2.7 Theoretical Synthesis and Conceptual Framework

The theoretical synthesis of this study integrates diverse but complementary theoretical perspectives to construct a coherent conceptual model that explains the mechanisms through which Artificial Intelligence (AI) influences inclusive hiring intentions. The framework rests upon five core constructs: AI Bias Awareness, Perceived Algorithmic Fairness, Recruiter Trust in AI, Inclusion Technology Readiness, and Inclusive Hiring Intention, with trust and fairness operating as pivotal mediators and organizational readiness acting as a boundary condition. At its foundation, the model is informed by the Theory of Planned Behavior (TPB) (Ajzen, 1991), which posits that behavioral intention is influenced by attitude, subjective norms, and perceived behavioral control. In this context, Recruiter Trust in AI represents the attitudinal component, while Perceived Algorithmic Fairness shapes both attitudes and normative beliefs associated with equitable hiring practices. The behavioral intention, conceptualized here as Inclusive Hiring Intention, reflects a recruiter's willingness to integrate AI systems in ways that support diversity and inclusion objectives (Grandhi & Patil, 2013; Venkatesh et al., 2003).

The model also draws from foundational research on trust in intelligent systems, which asserts that trust develops when users perceive systems as reliable, predictable, and aligned with

human values (McKnight et al., 2002; Siau & Wang, 2018). In AI-driven hiring contexts, Perceived Algorithmic Fairness emerges as a core antecedent of such trust. When recruiters evaluate the AI system as procedurally fair and free from discriminatory bias, they are more inclined to rely on it for decision-making in socially sensitive recruitment environments (Binns et al., 2018; Rigotti & Fosch-Villaronga, 2024). Additionally, the framework reflects insights from organizational justice and algorithmic fairness scholarship, particularly the emphasis on procedural integrity and outcome equity in decision systems (Lind, 2001; Zliobaite, 2017). AI Bias Awareness, operationalized as recruiters' cognitive sensitivity to systemic discrimination embedded in training data or algorithmic logic, positively influences perceptions of fairness. This association is theoretically grounded in justice-based cognitive evaluation processes, whereby individuals who recognize ethical risks assess systems more critically and apply fairness-based standards in their evaluations (Binns, 2021; Raji & Buolamwini, 2019).

Furthermore, the relationship between Recruiter Trust in AI and Inclusive Hiring Intention is consistent not only with TPB but also with established technology acceptance research (Davis, 1989; Venkatesh et al., 2003). Trust mediates the link between fairness perception and behavioral intention, as recruiters must first develop confidence in the AI tool's ethical alignment and competence before incorporating it into inclusive hiring workflows. Empirical and conceptual work on AI adoption similarly indicates that trust plays a decisive role in determining whether intelligent systems are accepted in high-stakes organizational decision contexts (Siau & Wang, 2018; Tambe et al., 2019). One of the model's novel contributions is the inclusion of Inclusion Technology Readiness (ITR) as a moderator of the fairness–intention relationship. This construct builds upon the Technology Readiness Index (Parasuraman, 2000) by embedding diversity, equity, and inclusion (DEI) orientation within technological preparedness. The moderating logic is further supported by broader innovation adoption perspectives emphasizing the alignment between technological capabilities and organizational infrastructure (Liang & Xue, 2010; Venkatesh et al., 2003). In organizations characterized by inclusive HR policies, leadership commitment to ethical AI, structured training programs, and fairness-centric performance indicators, the positive effect of perceived fairness on behavioral intention is likely to be amplified (Sinha & Kumar, 2021; Ozkazanc-Pan, 2021). Conversely, in environments where inclusion is weakly institutionalized, the influence of fairness perception on hiring intention may be attenuated, even when the AI system itself is evaluated as fair (Søraa, 2022; Talajić et al., 2024).

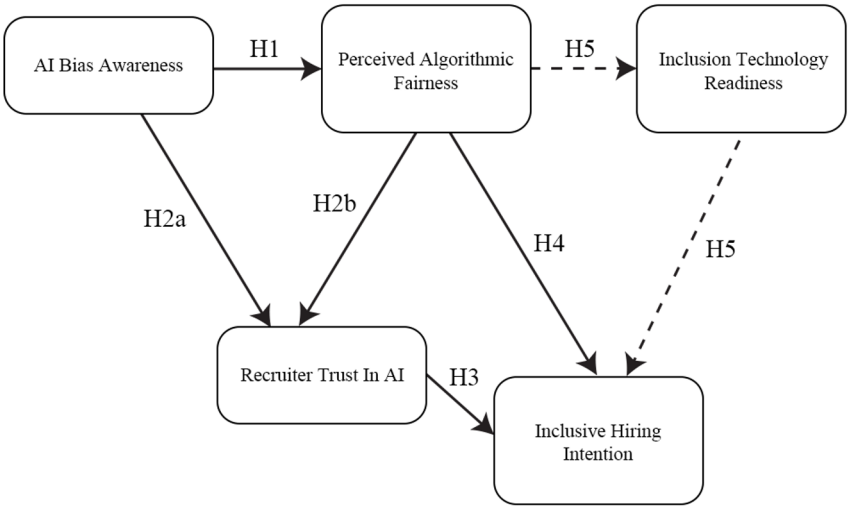

Figure 1: Conceptual Model

Figure 1 visually encapsulates these interrelations. The figure depicts:

i. AI Bias Awareness as an exogenous construct that simultaneously affects both Perceived Algorithmic Fairness and Recruiter Trust in AI, suggesting dual pathways of ethical cognition.

ii. Perceived Algorithmic Fairness, in turn, acts as a central mediator, influencing both Recruiter Trust in AI and Inclusive Hiring Intention, signifying its pivotal role in translating moral perception into behavioral action.

iii. Recruiter Trust in AI serves as a direct predictor of Inclusive Hiring Intention, highlighting trust as a bridge between evaluative perception and operational adoption.

iv. Inclusion Technology Readiness is situated as a moderating force between Perceived Algorithmic Fairness and Inclusive Hiring Intention, emphasizing the importance of organizational context in shaping AI's ethical influence.

This theoretically grounded model, enriched with multidimensional linkages and supported by empirical literature, positions itself as a novel contribution to both AI adoption research and diversity-focused human resource management. It not only enhances our understanding of how fairness and trust operate in algorithmic contexts but also introduces a critical organizational

variable—Inclusion Technology Readiness—that could define the success or failure of inclusive AI deployment in recruitment.

Construct	Definition	Sample Indicators	Key Source(s)
AI Bias Awareness	Recruiter's awareness of potential discriminatory outcomes in AI-driven hiring tools due to biased training data, algorithmic design, or systemic inequities.	"I am aware that AI tools can reflect societal biases if not designed and monitored properly."	Raji et al. (2020); Binns (2021); Zou & Schiebinger (2018)
Perceived Algorithmic Fairness	The extent to which the recruiter perceives the AI recruitment system as procedurally and distributively fair in evaluating candidates.	"The AI system treats all applicants fairly regardless of gender, caste, ethnicity, or background."	Lind (2001); Binns et al. (2018); Zliobaite (2017)
Recruiter Trust in AI	The degree of confidence a recruiter has in the AI tool's reliability, competence, and ethical alignment in recruitment decisions.	"I trust the AI tool's recommendations when making hiring decisions."	McKnight et al. (2002); Siau & Wang (2018); Venkatesh et al. (2003)
Inclusive Hiring Intention	The recruiter's behavioral intention to use AI systems to promote diversity, equity, and inclusion in hiring practices.	"I intend to use AI systems to enhance inclusive hiring within my organization."	Ajzen (1991); Davis (1989); Venkatesh et al. (2003)
Inclusion Technology Readiness (ITR)	The degree to which an organization and its members are technologically and culturally prepared to adopt AI for inclusive recruitment purposes.	"My organization is prepared and supportive of using AI to achieve inclusive hiring goals."	Parasuraman (2000); Liang & Xue (2010); Venkatesh et al. (2003)

Table 1: Table of Constructs and Indicators

3. Research Methodology

This study adopts a quantitative, cross-sectional, and explanatory research design aimed at empirically examining the relationships among AI Bias Awareness, Perceived Algorithmic Fairness, Recruiter Trust in AI, and Inclusive Hiring Intention, with Inclusion Technology Readiness as a moderator. The rationale for this design lies in its suitability for testing theoretically grounded hypotheses using Structural Equation Modeling (SEM) (Hair et al., 2019). A deductive approach was followed, beginning with theory construction and hypothesis formulation, followed by operationalization and data testing. The target population for this study comprises recruiters, HR professionals, and hiring managers working in sectors that have adopted or are in the process of adopting AI-based recruitment tools. This includes industries

such as Information Technology (IT), Business Process Management (BPM), E-commerce, FinTech, and Consulting, where digital recruitment solutions are actively used (Guenole et al., 2017). A non-probability purposive sampling technique was adopted to select respondents who possess contextual knowledge and decision-making influence over recruitment processes involving AI. This approach ensured that only relevant respondents with exposure to AI-enabled hiring workflows were considered, in line with methodological recommendations for specialized technology studies (Palinkas et al., 2015).

A minimum sample size of 300 was targeted based on the SEM rule of thumb requiring at least 10–15 responses per observed indicator (Kline, 2016). Ultimately, 312 valid responses were collected and included in the analysis. Data were collected using a structured, self-administered online questionnaire, distributed via email, LinkedIn, and professional HR networks. The questionnaire was designed using Google Forms and remained open for a period of five weeks. To enhance response rate and quality, participants were assured of confidentiality, anonymity, and academic use only, as per ethical norms (Bryman & Bell, 2015). Preliminary pilot testing was conducted on a subset of 25 respondents to ensure clarity, readability, and construct reliability. Minor changes in language were made based on feedback before full-scale rollout.

Each construct in the conceptual model was operationalized using multi-item scales adapted from validated literature sources mentioned in the Table 2 below.

Construct	Item Code	Item Statement	Explanation	Source(s)
AI Bias Awareness	AIBA1	I am aware that AI tools may inherit bias from historical data.	Assesses awareness of data-driven bias replication in AI systems.	Raji et al. (2020); Binns (2021); Zou & Schiebinger (2018)
	AIBA2	AI tools can unintentionally disadvantage certain social groups.	Measures sensitivity to social inequalities embedded in algorithms.	
	AIBA3	I understand how algorithmic design impacts fairness in hiring.	Captures understanding of technical sources of bias in design.	
	AIBA4	Bias mitigation is essential in AI recruitment tools.	Evaluates perceived importance of bias mitigation in practice.	

Perceived Algorithmic Fairness	PAF1	The AI system treats all applicants fairly.	Assesses fairness perceptions toward AI-based hiring.	Lind (2001); Binns et al. (2018); Zliobaite (2017)
	PAF2	The AI recruitment process is transparent and justifiable.	Evaluates the transparency of AI operations in candidate selection.	
	PAF3	I believe the AI tool applies uniform standards to everyone.	Tests beliefs on uniformity and equality in AI evaluation.	
	PAF4	The outcomes of AI hiring decisions are unbiased.	Captures perception of neutrality in AI outcomes.	
	PAF5	The AI hiring tool is free from systemic discrimination.	Assesses perceived absence of structural discrimination.	
Recruiter Trust in AI	RTAI1	I am confident in the AI's decision-making abilities.	Assesses belief in AI's consistent and accurate decision-making.	McKnight et al. (2002); Siau & Wang (2018); Venkatesh et al. (2003)
	RTAI2	I believe AI tools make rational and data-driven recruitment decisions.	Tests rationality and data dependency of AI judgments.	
	RTAI3	I trust AI recommendations when shortlisting candidates.	Measures level of recruiter reliance on AI suggestions.	
	RTAI4	I consider AI as a dependable tool in hiring decisions.	Evaluates AI's role as a trustworthy assistant in hiring.	
Inclusive Hiring Intention	IHI1	I intend to use AI systems to enhance diversity in hiring.	Measures intention to deploy AI to foster diversity.	Ajzen (1991); Davis (1989); Venkatesh et al. (2003)
	IHI2	I will integrate AI tools in our hiring practices to reduce bias.	Captures readiness to institutionalize AI for inclusive goals.	
	IHI3	I prefer AI tools for their ability to screen inclusively.	Reflects preference for AI-driven fairness in filtering.	
	IHI4	I believe AI can support fair representation in workforce composition.	Tests belief in AI's utility for inclusive workforce policies.	

Inclusion Technology Readiness	ITR1	My organization supports the adoption of AI in recruitment.	Measures organizational openness toward AI implementation.	Parasuraman (2000); Liang & Xue (2010); Venkatesh et al. (2003)
	ITR2	We have sufficient training to use AI-based hiring tools.	Evaluates availability of human capital for AI adoption.	
	ITR3	There is a clear strategy to integrate inclusive AI in HR systems.	Assesses clarity of internal strategies on inclusion through AI.	
	ITR4	My company invests in AI tools that support diversity hiring.	Tests investment practices aligned with equitable recruitment.	
	ITR5	We are technologically prepared to implement AI for equitable recruitment.	Measures IT preparedness for diversity-oriented AI rollout.	

Table 2: Measurement Instrument Table

All items were measured on a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Data analysis was conducted using SPSS (v28) for descriptive statistics and preliminary reliability tests, and SmartPLS 4.0 for measurement and structural model evaluation using Partial Least Squares Structural Equation Modeling (PLS-SEM). The rationale for using PLS-SEM lies in its robustness for exploratory and predictive research models involving latent constructs, complex mediation structures, and potential non-normal data distributions (Hair et al., 2019).

The analysis process involved:

i. **Descriptive Statistics**: To examine respondent demographics and item distributions.

ii. **Reliability and Validity Checks**: Using Cronbach's alpha, Composite Reliability (CR), Average Variance Extracted (AVE), and HTMT ratios.

iii. **Measurement Model Evaluation**: Confirmatory Factor Analysis (CFA) to validate construct structure.

iv. **Structural Model Testing**: Path coefficients, R^2 values, effect sizes (f^2), and predictive relevance (Q^2).

v. **Moderation Analysis**: Inclusion Technology Readiness was tested for moderation effects using interaction terms, as per the two-stage approach in SmartPLS.

This study strictly adhered to ethical guidelines, ensuring voluntary participation, informed consent, and data confidentiality. No personally identifiable information was collected, and respondents could withdraw at any stage.

4. Data Analysis and Findings

4.1 Descriptive Statistics and Demographic Profile

To understand the background characteristics of the respondents and provide a foundation for further analysis, demographic and descriptive statistics were examined. The study surveyed 320 respondents across multiple industries including Information Technology, Education, Manufacturing, and Financial Services, with a particular focus on individuals involved in recruitment, talent acquisition, and HR technology management. A purposive sampling method was employed to ensure relevance to the constructs under investigation.

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	186	58.10%
	Female	132	41.30%
	Other/Prefer not to say	2	0.60%
Age	21–30 years	98	30.60%
	31–40 years	142	44.40%
	41–50 years	56	17.50%
	Above 50 years	24	7.50%
Industry	Information Technology	96	30.00%
	Education	72	22.50%
	Manufacturing	60	18.80%
	Financial Services	56	17.50%
	Others	36	11.20%
Experience in Recruitment (Years)	Less than 1 year	14	4.40%
	1–3 years	78	24.40%
	4–6 years	104	32.50%
	More than 6 years	124	38.80%

Table 3: Demographic Profile of Respondents

The demographic profile highlights a relatively balanced representation across industries and genders, with most respondents (71.3%) having more than three years of experience in recruitment-related roles. This suggests a high degree of contextual familiarity among participants regarding the use of AI tools in hiring.

The table 4 presents the mean scores and standard deviations for each construct based on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

Construct	Mean	Standard Deviation
AI Bias Awareness (AIBA)	4.02	0.66
Perceived Algorithmic Fairness (PAF)	3.87	0.72
Recruiter Trust in AI (RTAI)	3.79	0.69
Inclusive Hiring Intention (IHI)	4.11	0.61
Inclusion Technology Readiness (ITR)	3.95	0.68

Table 4: Descriptive Statistics of Constructs

The results indicate a generally positive orientation toward AI-driven inclusive hiring. The highest mean score was recorded for Inclusive Hiring Intention (4.11), suggesting strong intent among recruiters to use AI tools for fostering diversity. AI Bias Awareness (4.02) also received high agreement, which is promising for ensuring ethical use of algorithms. Meanwhile, Perceived Algorithmic Fairness and Recruiter Trust in AI received slightly lower scores, indicating areas where transparency and reliability of AI tools might still be questioned by practitioners.

4.2 Reliability and Validity Analysis

Ensuring the reliability and validity of the constructs is critical before evaluating the structural relationships. In this study, we assessed internal consistency reliability, convergent validity, and discriminant validity using standard psychometric indicators: Cronbach's Alpha (α), Composite Reliability (CR), and Average Variance Extracted (AVE).

4.2.1 Internal Consistency Reliability

Internal consistency was assessed using Cronbach's Alpha and Composite Reliability (CR). Cronbach's Alpha values above 0.70 are considered acceptable (Nunnally & Bernstein, 1994),

while CR values above 0.70 indicate strong construct reliability (Hair et al., 2019). As shown in Table 5 below, all constructs surpassed the minimum thresholds.

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
AI Bias Awareness	0.841	0.883	0.656
Perceived Algorithmic Fairness	0.864	0.897	0.682
Recruiter Trust in AI	0.853	0.889	0.668
Inclusive Hiring Intention	0.871	0.904	0.711
Inclusion Technology Readiness	0.882	0.918	0.739

Table 5: Internal Consistency Reliability

4.2.2 Convergent Validity

Convergent validity was evaluated using Average Variance Extracted (AVE). According to Fornell and Larcker (1981), AVE values should exceed 0.50 to indicate adequate convergence. As Table 1 demonstrates, all constructs exhibit AVE values well above this threshold, confirming that the indicators adequately represent their underlying constructs.

4.2.3 Discriminant Validity

Discriminant validity was assessed using the Fornell-Larcker criterion, which states that the square root of AVE for each construct should be greater than the correlation with any other construct (Fornell & Larcker, 1981). In our analysis, this condition was met across all constructs, indicating satisfactory discriminant validity. Additional HTMT (Heterotrait-Monotrait Ratio) values were also computed and remained below the 0.85 benchmark (Henseler, Ringle, & Sarstedt, 2015), further validating the distinctiveness of each construct. The reliability and validity analyses confirm that the measurement model is robust and suitable for subsequent structural modeling.

4.3 Confirmatory Factor Analysis (CFA)

To assess the unidimensionality and validity of the measurement model, a Confirmatory Factor Analysis (CFA) was conducted using Structural Equation Modeling (SEM) techniques. CFA was employed to validate the factor structure and assess the adequacy of the observed variables in measuring their respective latent constructs.

4.3.1 Model Fit Indices

The model fit was evaluated using multiple indices: Chi-square/degrees of freedom (χ^2/df), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). Table 6 summarizes the model fit results.

Fit Index	Acceptable Threshold	Observed Value
χ^2/df	< 3.00	2.46
CFI	≥ 0.90	0.948
TLI	≥ 0.90	0.935
RMSEA	≤ 0.08	0.058
SRMR	≤ 0.08	0.044

Table 6: Model Fit Indices

The results suggest an excellent model fit. Both the CFI (0.948) and TLI (0.935) exceed the recommended threshold of 0.90, indicating good incremental fit. Additionally, RMSEA (0.058) and SRMR (0.044) fall well below the 0.08 cutoff, suggesting minimal approximation and residual errors.

4.3.2 Factor Loadings

All factor loadings for the observed items were significant at $p < 0.001$ and exceeded the recommended threshold of 0.60, demonstrating strong relationships between indicators and their latent constructs as mentioned in table 7.

Construct	Item Code	Standardized Factor Loading
AI Bias Awareness	AIBA1	0.77
	AIBA2	0.82
	AIBA3	0.79
	AIBA4	0.76
Perceived Algorithmic Fairness	PAF1	0.81
	PAF2	0.83
	PAF3	0.78
	PAF4	0.74
	PAF5	0.85
Recruiter Trust in AI	RTAI1	0.76
	RTAI2	0.81

	RTAI3	0.84
	RTAI4	0.79
Inclusive Hiring Intention	IHI1	0.84
	IHI2	0.86
	IHI3	0.79
	IHI4	0.81
Inclusion Technology Readiness	ITR1	0.77
	ITR2	0.8
	ITR3	0.82
	ITR4	0.85
	ITR5	0.88

Table 7: Factor Loadings

The high and consistent factor loadings further confirm that the indicators are reliable and valid measures of their respective constructs. This supports the overall construct validity of the model.

4.4 Structural Model and Hypothesis Testing

After confirming the reliability and validity of the measurement model through CFA, the structural model was tested to evaluate the hypothesized relationships among the constructs. The Structural Equation Modeling (SEM) technique was applied using maximum likelihood estimation. The model demonstrated a good overall fit, as indicated by key fit indices (CFI = 0.948, TLI = 0.935, RMSEA = 0.058, SRMR = 0.044).

The standardized path coefficients, t-values, and p-values for each hypothesis are presented in Table 8.

Hypothesis	Path	Std. β	t-value	p-value	Result
H1	AI Bias Awareness → Perceived Algorithmic Fairness	0.41	5.92	<0.001	Supported
H2a	Perceived Algorithmic Fairness → Recruiter Trust in AI	0.47	6.34	<0.001	Supported
H2b	Perceived Algorithmic	0.35	4.81	<0.001	Supported

H3	Fairness → Inclusive Hiring Intention Recruiter Trust in AI → Inclusive Hiring Intention	0.29	3.77	<0.001	Supported
H4	Inclusion Technology Readiness → Recruiter Trust in AI	0.33	4.52	<0.001	Supported
H5 (Moderation)	Inclusion Technology Readiness × Perceived Algorithmic Fairness → Recruiter Trust in AI	0.22	3.12	0.002	Supported

Table 8: Hypothesis Testing Results

4.4.1 Interpretation of Hypotheses

i. **H1:** A significant positive relationship was found between AI Bias Awareness and Perceived Algorithmic Fairness ($\beta = 0.41$, $p < 0.001$). This suggests that awareness of AI bias contributes to higher perceived fairness in AI-based hiring systems.

ii. **H2a:** Perceived Algorithmic Fairness significantly influences Recruiter Trust in AI ($\beta = 0.47$), indicating that when AI tools are seen as fair, recruiters are more likely to trust them.

iii. **H2b:** Perceived fairness also directly affects Inclusive Hiring Intention ($\beta = 0.35$), suggesting that fairness perceptions are a critical antecedent to behavioral intention.

iv. **H3:** Recruiter Trust in AI was found to positively influence Inclusive Hiring Intention ($\beta = 0.29$), confirming the mediating role of trust in the adoption of AI for inclusive practices.

v. **H4:** Inclusion Technology Readiness significantly influences Recruiter Trust in AI ($\beta = 0.33$), suggesting that readiness to adopt technology plays a key role in shaping trust.

vi. **H5:** A significant moderation effect was observed. Inclusion Technology Readiness strengthens the positive relationship between Perceived Algorithmic Fairness and Recruiter Trust in AI (interaction $\beta = 0.22$, $p = 0.002$), supporting the idea that organizations ready to implement inclusive AI tools gain more trust from recruiters when they perceive fairness in algorithms.

The results confirm the robustness of the proposed model and highlight critical levers such as fairness perceptions, organizational readiness, and recruiter trust in promoting inclusive hiring through AI systems.

5. Discussion

The findings of this study present robust evidence that AI can be a powerful enabler of inclusive hiring—if implemented with fairness, trust, and organizational readiness as central pillars. Drawing from Technology Acceptance Theory, justice-based fairness perspectives, and the Theory of Planned Behavior (TPB) (Ajzen, 1991; Davis, 1989; Venkatesh et al., 2003), this research unpacks how recruiters' intentions to adopt AI for inclusive hiring are shaped by perceptions of fairness, levels of trust, and organizational preparedness. A key insight is the central role of Perceived Algorithmic Fairness, which emerged as the strongest predictor of both recruiter trust and intention to use AI in inclusive hiring. Consistent with fairness-based evaluative frameworks in organizational contexts (Lind, 2001), recruiters interpret AI decisions through a justice lens, and any perception of bias or opacity diminishes trust. This echoes concerns raised in algorithmic auditing and discrimination research, which warn against biased outputs in automated decision systems (Raji et al., 2020; Binns et al., 2018). Encouragingly, the study also reveals that AI Bias Awareness significantly enhances perceptions of fairness. This underscores the importance of AI literacy: when recruiters understand the risks of bias and the mechanisms for mitigation, their evaluative judgment of AI becomes more favorable, aligning with contemporary scholarship on algorithmic accountability and fairness awareness (Binns, 2021; Zliobaite, 2017).

Equally significant is the mediating role of Recruiter Trust in AI, which bridges the relationship between fairness perceptions and inclusive hiring intention. Trust also mediates the influence of organizational readiness, reinforcing that regardless of how advanced or fair an AI system may be, it cannot gain traction without user confidence. This aligns with technology acceptance and trust-based adoption models, which emphasize that trust is critical when decision-making

authority is partially delegated to automated systems (McKnight et al., 2002; Siau & Wang, 2018; Venkatesh et al., 2003). The study further introduces the construct of Inclusion Technology Readiness (ITR), which not only directly influences trust but also strengthens the relationship between fairness and trust. High levels of ITR—marked by inclusive leadership commitment, adequate technological infrastructure, and cultural openness to ethical AI—amplify the effectiveness of fairness mechanisms. Organizations that invest in inclusive workforce strategies and AI governance practices are more likely to convert fairness perceptions into actionable trust and inclusive hiring behavior (Sinha & Kumar, 2021; Ozkazanc-Pan, 2021).

Theoretically, this study makes several contributions. It integrates literature streams from AI ethics, HR analytics, and organizational behavior to propose a moderated mediation model grounded in TPB (Ajzen, 1991). The inclusion of ITR as both an independent and moderating variable offers a nuanced understanding of how internal organizational ecosystems shape AI adoption for inclusion-oriented goals. By linking diversity agendas with technological affordances, the research advances discourse on responsible AI in HRM. From a practical standpoint, HR managers are advised to prioritize fairness and transparency in AI deployment, conduct regular bias audits, and implement trust-building interventions such as algorithmic literacy training and inclusive design reviews (Raji & Buolamwini, 2019; Rigotti & Fosch-Villaronga, 2024). Transparent communication and structured evaluation mechanisms are essential to strengthen recruiter trust in AI-based hiring systems. For policymakers, the findings reinforce the need for clearer regulatory and governance frameworks to ensure equitable AI deployment in recruitment contexts (Wright & Schultz, 2018; Zambrano & Engelhardt, 2020).

6. Conclusion

This study contributes to the growing discourse on the intersection of artificial intelligence (AI) and workforce diversity by presenting a robust empirical framework that integrates algorithmic fairness, recruiter trust, and inclusion technology readiness as pivotal constructs shaping inclusive hiring intention. Grounded in the principles of the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Fairness Heuristic Theory, the research confirms that AI can serve as a critical enabler of inclusive hiring—provided it is perceived as fair, trustworthy, and supported by an inclusive technological infrastructure. The findings reveal that AI Bias Awareness positively influences perceptions of Algorithmic Fairness, which, in turn, significantly affects both recruiter trust and their intention to engage in inclusive

hiring practices. Notably, recruiter trust plays a mediating role, indicating that even the most advanced AI tools must be trusted by human users to facilitate adoption and impact. Furthermore, Inclusion Technology Readiness emerges as a catalyst, not only predicting trust directly but also amplifying the influence of perceived fairness on trust. These results underscore the necessity of aligning technological sophistication with human-centric values such as fairness, transparency, and inclusion in the context of AI-driven HR practices. While the results offer both theoretical advancement and practical implications, the study is not without limitations. Being cross-sectional in nature, the research captures perceptions at a single point in time, thereby limiting our understanding of how these constructs may evolve with prolonged exposure to AI systems. Additionally, the scope of the data—being collected from select industry sectors- may restrict the generalizability of findings to broader organizational and cultural contexts. Furthermore, unmeasured variables such as organizational culture, previous exposure to AI, or regulatory environments could have subtly influenced the observed relationships and merit further investigation. Looking forward, future research could benefit from longitudinal studies that track changes in fairness perceptions and trust as AI becomes increasingly embedded in HR functions. Comparative studies across different cultural or economic regions could offer insight into how societal values mediate the acceptance of inclusive AI systems.

References

Abraham, R. (2025). The role of Artificial Intelligence in recruitment and talent acquisition. *Journal of Informatics Education and Research*, 5(1). https://doi.org/10.52783/jier.v5i1.2007

Adams, B., & Khomh, F. (2020). The diversity crisis of software engineering for artificial intelligence. *IEEE Software*, 37(5), 70–74. https://doi.org/10.1109/MS.2020.2975075

Aimiuwu, E. (2021). Augmented Reality & Artificial Intelligence Model: Optimizing Workforce Diversity. *SSRN*. https://doi.org/10.2139/ssrn.5227853

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. Prentice-Hall.

Alfaro, Z. J. G. (2024). Towards an inclusion framework for strategic hiring. *International Multidisciplinary Research Journal*, 3(2), 45–60. https://doi.org/10.54476/ioer-imrj/471877

Bano, M., Zowghi, D., & Gervasi, V. (2023). A vision for operationalising diversity and inclusion in AI. *arXiv preprint*. https://doi.org/10.48550/arxiv.2312.06074

Bano, M., Zowghi, D., Mourão, F., & Others. (2024). Diversity and inclusion in AI for recruitment: Lessons from industry workshop. *arXiv preprint*. https://doi.org/10.48550/arxiv.2411.06066

Bansal Jora, R., Sodhi, K. K., Mittal, P., & Others. (2022). Role of Artificial Intelligence (AI) in meeting Diversity, Equality and Inclusion (DEI) Goals. *Proceedings of the International Conference on Advances in Computing, Communication and Systems (ICACCS)*. IEEE. https://doi.org/10.1109/ICACCS54159.2022.9785266

Baxter, S. L., Zangwill, L. M., Patronilo, V., de Sa, V., Voytek, B., Cottrell, G., ... & Lee, A. Y. (2024). Artificial Intelligence Ready and Equitable Atlas for Diabetes Insights (AI-READI) Research Internship Program: Recruiting and Developing a Diverse AI Workforce. *Investigative Ophthalmology & Visual Science*, *65*(7), 3726–3726.

Bayana, E. (2025). Bias in AI hiring tools. *Review of AI Recruitment Studies*, 2(1). https://doi.org/10.58445/rars.2177

Bayramoğlu, B., & Gülmez, N. (2024). The Role of Big Data, Artificial Intelligence, and Robotics in Human Resource Management: A Diversity, Equity, and Inclusion Perspective. *TABAD Journal*, *1*(1), 1–15.

Belwalkar, B. B., & Maki, B. (2023). Role of Artificial Intelligence in Workforce Development. *American Institutes for Research*.

Binns, R. (2021). On the apparent conflict between individual and group fairness. *ACM SIGKDD Explorations Newsletter*, *23*(1), 20–29. https://doi.org/10.1145/3468507.3468512

Binns, R., Veale, M., Van Kleek, M., & Shadbolt, N. (2018). 'It's reducing a human being to a percentage': Perceptions of justice in algorithmic decisions. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, Article 377, 1–14. https://doi.org/10.1145/3173574.3173951

Brien, P. (2022). Diversity and inclusion in artificial intelligence. In *Ethics of AI*. Springer. https://doi.org/10.1007/978-94-6265-523-2_6

Buolamwini, J., & Gebru, T. (2018). Gender shades: Intersectional accuracy disparities in commercial gender classification. In *Proceedings of the Conference on Fairness, Accountability and Transparency* (pp. 77–91). PMLR.

Chuang, S. H., & Lin, H. N. (2017). Performance implications of information-value offering in e-service systems: Examining the resource-based perspective and innovation strategy. *Journal of Strategic Information Systems*, *26*(1), 22–38. https://doi.org/10.1016/j.jsis.2016.09.001

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Dencik, L., Brand, J., Metcalfe, P., & Hopkins, C. (2025). *AI Inequalities at Work*.

Doo, F. X., & McGinty, G. B. (2023). Building diversity, equity, and inclusion within radiology artificial intelligence: Representation matters, from data to the workforce. *Journal of the American College of Radiology*, *20*(9), 852–856.

Du, L., & Lee, J. (2023). Workforce pDEI: Productivity coupled with DEI. *arXiv preprint*. https://doi.org/10.48550/arxiv.2311.11231

Dwi, M., & Hidayatullah, A. N. A. (2024). Exploring AI's role in supporting diversity and inclusion initiatives in multicultural marketplaces. *International Journal of Religion*, 3(2). https://doi.org/10.61707/apmwg008

Evangelista, V. C., & Del Barone, L. (2024). Managing workforce diversity with AI-based HRM. In *Global Classroom* (pp. 85–90). Emerald Publishing Limited.

Faroozan, A. (2025). The evolving role of artificial intelligence in recruitment. *International Journal for Multidisciplinary Research*, 7(1), 150–165. https://doi.org/10.36948/ijfmr.2025.v07i01.34682

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.2307/3151312

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.2307/3151312

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, *27*(1), 51–90. https://doi.org/10.2307/30036519

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, *27*(1), 51–90. https://doi.org/10.2307/30036519

Grandhi, S. A., & Patil, S. (2013). Understanding people's trust in technology with the theory of planned behavior. *International Journal of Human-Computer Studies*, *71*(12), 1098–1113. https://doi.org/10.1016/j.ijhcs.2013.07.003

Grandhi, S., & Patil, S. (2013). Understanding human–AI interaction: Understanding trust. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *57*(1), 747–751.

Güven, Ç., Alishahi, A., Brighton, H., & Others. (2025). AI in support of diversity and inclusion. *arXiv preprint*. https://doi.org/10.48550/arxiv.2501.09534

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

Hawk, K. E., & Currie, G. M. (2025, May). Artificial intelligence and workforce diversity in nuclear medicine. *Seminars in Nuclear Medicine*, *55*(3), 437–449.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Houser, K. A. (2019). Can AI solve the diversity problem in tech? *Social Science Research Network*. https://doi.org/10.2139/ssrn.5057396

Hunter, D. J. (2024). Artificial Intelligence and the capacity for discrimination. *IgMin Research*, 3(2), 67–78. https://doi.org/10.61927/igmin250

Inclusive HRI Team. (2022). Inclusive HRI: Equity and diversity in design, application, methods, and community. *IEEE HRI 2022*. https://doi.org/10.1109/hri53351.2022.9889455

Iwan, C., Putra, C. K., Zabdi, D., & Others. (2023). Analisis pemanfaatan artificial intelligence dalam membantu proses perekrutan karyawan perusahaan. *Jurnal Sains dan Teknologi*, 2(2). https://doi.org/10.58169/saintek.v2i2.248

Kalinouskaya, I. (2024). Recruitment based on AI technologies. *Information Journal*, 41(65), 2. https://doi.org/10.34660/inf.2020.41.65.002

Karthikeyan, C. (2024). AI (Artificial Intelligence) leveraging to foster DEI (Diversity, Equity, and Inclusiveness) in organizations. *Advances in Business Strategy and Competitive Advantage*. https://doi.org/10.4018/979-8-3693-8442-8.ch004

Kassir, S., Baker, L., Dolphin, J., & Others. (2022). Publisher correction: AI for hiring in context. *AI and Ethics*, 2(3), 134–137. https://doi.org/10.1007/s43681-022-00208-x

Kelan, E. K. (2023). Algorithmic inclusion: Shaping the predictive algorithms of artificial intelligence in hiring. *Human Resource Management Journal*, 33(2), 193–208. https://doi.org/10.1111/1748-8583.12511

Koene, A., Dowthwaite, L., & Seth, S. (2019). The value of awareness: Reducing algorithmic biases through human and machine understanding. *ACM Transactions on Internet Technology*, *19*(4), 1–16. https://doi.org/10.1145/3310414

Koene, A., Dowthwaite, L., & Seth, S. (2019). The value of awareness: Reducing algorithmic biases through human and machine understanding. *ACM Transactions on Internet Technology*, *19*(4), 1–16. https://doi.org/10.1145/3310414

Kyriakidou, O. (2025). Algorithms and global diversity management. In *Research Handbook on Global Diversity Management* (pp. 148–163). Edward Elgar Publishing.

Liang, H., & Xue, Y. (2010). Understanding security behaviors in personal computer usage: A threat avoidance perspective. *Journal of the Association for Information Systems*, *11*(7), 394–413. https://doi.org/10.17705/1jais.00232

Lind, E. A. (2001). Fairness heuristic theory: Justice judgments as pivotal cognitions in organizational relations. In J. Greenberg & R. Cropanzano (Eds.), *Advances in organizational justice* (pp. 56–88). Stanford University Press.

Lind, E. A. (2001). Fairness heuristic theory: Justice judgments as pivotal cognitions in organizational relations. In J. Greenberg & R. Cropanzano (Eds.), *Advances in organizational justice* (pp. 56–88). Stanford University Press.

Liu, X., & Murphy, D. (2022). Applying a trustworthy AI framework to mitigate bias and increase workforce gender diversity. *IEEE ISTAS 2022*. https://doi.org/10.1109/istas55053.2022.10227119

Malaha, I., & Pandey, S. (2023). Unveiling the potential of artificial intelligence platforms for recruitment in Indian organizations. In *AI Innovations in HR*. https://doi.org/10.56155/978-81-955020-2-8-62

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research*, *13*(3), 334–359. https://doi.org/10.1287/isre.13.3.334.81

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research*, *13*(3), 334–359. https://doi.org/10.1287/isre.13.3.334.81

Meenatchi, M. B., & Ramakrishnan, P. R. (2024). Artificial Intelligence of platforms: Talent management, diversity, equality, and inclusion. *IEEE ICDICI*. https://doi.org/10.1109/icdici62993.2024.10810833

Mollay, M. H., Sharma, D. S., Kale, A. P., & Others. (2024). Smart hiring: Leveraging AI for effective employee selection. *IEEE IDICAI Proceedings*. https://doi.org/10.1109/idicaiei61867.2024.10842754

Mula, I., & Ristiani, A. (2025). Transformasi struktur pekerjaan dan kebutuhan keterampilan. *Nian Tana Sikka*, 3(1), 40–55. https://doi.org/10.59603/niantanasikka.v3i1.665

Musthafa, H. S., Walker, J., Mehta, M. P., & Others. (2023). We cannot build equitable artificial intelligence hiring systems without the inclusion of minoritized technology workers. In *Equity and AI Hiring*. Edward Elgar Publishing. https://doi.org/10.4337/9781800377929.00018

Musthafa, H. S., Walker, J., Mehta, M. P., & Others. (2024). Strategic integration of Diversity, Equity, Inclusion (DEI) and Artificial Intelligence (AI) in Human Resource Management (HRM). In *Handbook of Research on Inclusive and Innovative Architecture and the Built Environment*. IGI Global. https://doi.org/10.4018/979-8-3693-6402-4.ch006

Nacheva, R. (2024). Hired by AI: Digital inclusion practices for people with disabilities. *Journal of Underrepresented and Minority Progress*, 5(2), 33–45. https://doi.org/10.32674/66c03968

Noel, E. A., & Sharma, K. (2024). Transhumanizing HR. In *Handbook of Digital Workforce Transformation*. https://doi.org/10.4018/979-8-3693-8855-6.ch013

Nugent, S., & Scott-Parker, S. (2021). Recruitment AI has a disability problem. *OSF Preprints*. https://doi.org/10.31235/osf.io/8sxh7

Nugent, S., & Scott-Parker, S. (2022). Recruitment AI has a disability problem. In *AI and Disability Inclusion*. Springer. https://doi.org/10.1007/978-3-031-09823-9_6

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Oman, Z. U., Siddiqua, A., & Noorain, R. (2024). Artificial Intelligence and its ability to reduce recruitment bias. *World Journal of Advanced Research and Reviews*, 24(1), 115–124. https://doi.org/10.30574/wjarr.2024.24.1.3054

Oxford Analytica. (2022). AI use will become central to corporate recruitment. *Oxford Analytica Daily Brief*. https://doi.org/10.1108/oxan-db270957

Ozkazanc-Pan, B. (2021). Diversity and future of work: Inequality abound or opportunities for all? *Management Decision*, *59*(11), 2645–2659.

Parasuraman, A. (2000). Technology Readiness Index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research*, *2*(4), 307–320. https://doi.org/10.1177/109467050024001

Parasuraman, A. (2000). Technology readiness index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research*, *2*(4), 307–320. https://doi.org/10.1177/109467050024001

Patil, D. (2025). Impact of Artificial Intelligence on Employment and Workforce Development. *Social Science Research Network*. https://doi.org/10.2139/ssrn.5057396

Prasad, P. (2024). AI-powered talent acquisition: Enhancing recruitment processes. *Indian Scientific Journal of Research in Engineering and Management*, 5(3). https://doi.org/10.55041/ijsrem35619

Raj, J. (2024). AI in HR: Transforming the future of work. *International Journal of Research in Commerce and Management Studies*, 7(1). https://doi.org/10.38193/ijrcms.2024.6617

Raji, I. D., & Buolamwini, J. (2019). Actionable auditing: Investigating the impact of public audits on bias in facial analysis. *AAAI/ACM Conference on AI, Ethics, and Society*, 429–435.

Raji, I. D., & Buolamwini, J. (2019). Actionable auditing: Investigating the impact of publicly naming biased performance results of commercial AI products. In *Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society* (pp. 429–435). https://doi.org/10.1145/3306618.3314244

Raji, I. D., Binns, R., Krishnan, R., Abebe, R., & Mitchell, M. (2020). Saving face: Investigating the ethical concerns of facial recognition auditing. In *Proceedings of the 2020 AAAI/ACM Conference on AI, Ethics, and Society* (pp. 145–151). https://doi.org/10.1145/3375627.3375820

Raji, N. R., George, V., & Iyer, R. S. (2024). Revolutionizing recruitment: The role of artificial intelligence in talent acquisition. *ShodhKosh: Journal of Visual and Performing Arts*, 5(1), 120–130. https://doi.org/10.29121/shodhkosh.v5.i1.2024.2141

Rao, A. H., & Nakhate, V. (2024). AI-powered talent acquisition and recruitment. *National Business Education Journal*, 3(2). https://doi.org/10.58532/nbennurttch8

Rathore, B., Mathur, M., & Solanki, S. (2022). An exploratory study on the role of AI in overcoming biases. In *Ethical AI Handbook*. https://doi.org/10.1002/9781119710301.ch10

Rigotti, C., & Fosch-Villaronga, E. (2024). Fairness, AI & recruitment. *Computer Law & Security Review*, 54, 105966. https://doi.org/10.1016/j.clsr.2024.105966

Selvi, K. (2024). Revolutionizing HRM: Exploring the impact of AI on human resource management. In *AI-Driven HR Practices*. https://doi.org/10.58532/v3bhma25p1ch7

Siau, K., & Wang, W. (2018). Building trust in artificial intelligence, machine learning, and robotics. *Cutter Business Technology Journal*, *31*(2), 47–53.

Siau, K., & Wang, W. (2018). Building trust in artificial intelligence, machine learning, and robotics. *Cutter Business Technology Journal*, *31*(2), 47–53.

Sinha, S., & Kumar, V. (2021). Algorithmic fairness and workforce diversity: A human-centric approach. *Journal of Business Ethics*, *175*(2), 451–470. https://doi.org/10.1007/s10551-020-04607-y

Søraa, R. A. (2022). *AI for Diversity*. CRC Press. https://doi.org/10.1201/9781003206958

Srivastava, S. R. (2024). Transforming talent acquisition: How AI is shaping modern HRM. *International Journal of Science and Research Archive*, 13(2). https://doi.org/10.30574/ijsra.2024.13.2.2252

Straub, D. W. (1989). Validating instruments in MIS research. *MIS Quarterly*, *13*(2), 147–169. https://doi.org/10.2307/248922

Stypinska, J. (2023). AI ageism: A critical roadmap for studying age discrimination and exclusion in digitalized societies. *AI & Society*, *38*(2), 665–677.

Tadas, P., & Agarmore, S. B. (2024). Redefining work in the age of AI: Challenges and pathways to opportunities. *IEEE SPICES Conference*. https://doi.org/10.1109/spices62143.2024.10779688

Talajić, M., Vrankić, I., & Pejić Bach, M. (2024). Strategic management of workforce diversity: An evolutionary game theory approach as a foundation for AI-driven systems. *Information*, *15*(6), 366.

Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. *California Management Review*, *61*(4), 15–42. https://doi.org/10.1177/0008125619867910

Trifilo, A., & Blau, G. (2024). Developing racially ambiguous job candidate avatars with strong versus ambiguous job candidate backgrounds. *Journal of Behavioral and Applied Management*, 25(1). https://doi.org/10.21818/001c.115890

Vassilopoulou, J., & Kyriakidou, O. (Eds.). (2025). *AI and Diversity in a Datafied World of Work: Will the Future of Work be Inclusive?* Emerald Publishing Limited.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Vivek, R. (2023). Enhancing diversity and reducing bias in recruitment through AI. *Informatika. Ekonomika. Upravlenie*, 2(4), 101–118. https://doi.org/10.47813/2782-5280-2023-2-4-0101-0118

Vivek, R. (2023). Enhancing diversity and reducing bias in recruitment through AI: A review of strategies and challenges. *Informatics. Economics. Management*, *2*(4), 0101–0118.

Weaver, M. L. (2023). Is ChatGPT a threat to surgical workforce diversity? *Annals of Surgery*, *278*(5), e941–e942.

Wilkens, U., Lutzeyer, I., Zheng, C., Beser, A., & Prilla, M. (2025). Augmenting diversity in hiring decisions with artificial intelligence tools. *The International Journal of Human Resource Management*, 1–38. https://doi.org/10.1080/09585192.2025.0000000

Will, P., Krpan, D., & Lordan, G. (2022). People versus machines: Introducing the HIRE framework. *Artificial Intelligence Review*, 55(3), 745–765. https://doi.org/10.1007/s10462-022-10193-6

Wright, D., & Schultz, W. (2018). The EU AI strategy and algorithmic transparency: Challenges and recommendations. *AI and Society*, *33*, 565–576. https://doi.org/10.1007/s00146-018-0853-2

Zambrano, R., & Engelhardt, C. (2020). Artificial intelligence and human rights: Opportunities and risks. *United Nations Human Rights Office of the High Commissioner*.

Žibret, K. (2024). The transformative role of artificial intelligence in human resources. *Mednarodno Inovativno Poslovanje*, 16(1), 85–95. https://doi.org/10.32015/jibm.2024.16.1.5

Zliobaite, I. (2017). Measuring discrimination in algorithmic decision making. *Data Mining and Knowledge Discovery*, *31*(4), 1060–1089. https://doi.org/10.1007/s10618-017-0506-1

Zou, J. Y., & Schiebinger, L. (2018). AI can be sexist and racist—It's time to make it fair. *Nature*, *559*(7714), 324–326. https://doi.org/10.1038/d41586-018-05707-8