iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

FROM BIAS TO BRILLIANCE: LEVERAGING AI TO REDUCE THE BIAS IN HIRING

D. Jyothi,
G. Sneha,
D. Jaya Lakshmi
B. Tech Students, Dept. of Computer Science and Engineering,
R.V.R&J.C College of Engineering, Chowdavaram, Guntur, Andhra Pradesh, India.

M. Vasavi.
Professor, Dept. of Computer Science and Engineering
R.V.R&J.C College of Engineering, Chowdavaram, Guntur, Andhra Pradesh, India.

ABSTRACT
In the quickly changing field of talent acquisition and human resources, the effect of artificial intelligence (henceforth, AI) on biases in hiring has become an important and revolutionary field of research. Thus, the purpose of this study is to critically assess how AI use affects hiring prejudices, especially in the context of China. A poll of 423 respondents employed in the manufacturing industry was used to get the data. We employ multiple diagnostics (such as reliability and collinearity tests) and a cross-sectional dataset. The empirical results obtained through the use of multiple regression approaches indicated that Al usage is changing the employment process by providing creative ways to address prejudices that have dominated it for many years. However, in addition to the usage of AI, human interaction is essential in the hiring process. While AI can effectively handle activities like data analysis and applicant screening, human judgment adds crucial elements to the hiring process. Human recruiters are able to evaluate a candidate's emotional intelligence, cultural fit, and soft skills because these attributes are Challenging to comprehend AI. The study's policy implications suggest that companies might develop a hiring process that is not just efficient and objective but also thoughtful, moral, and in line with the company's beliefs and objectives by fusing the advantages of AI efficiency with human intuition.

Keywords:
Artificial intelligence (AI), human resource management, recruitment biases.

I.INTRODUCTION

The globe has never been more intertwined. Companies are undergoing radical change in preparation for rapidly advancing technological advancements as a means of competing in the global labour market [1], [2]. There is fierce competition for the few, top-tier employees required for companies to maintain their competitiveness globally and meet the constantly increasing needs of customers, in addition to the concentration of job duties during the internationalization era [3]. Since it can be expensive to hire the incorrect people or to reject modifications to the conventional recruiting process, Unfortunately, finding, hiring, and retaining exceptional personnel is now more difficult than ever due to worldwide workforce shortages [5].

One of the most important recent developments in the business world is the growing importance placed on human resources. People are vital to businesses because they provide a variety of viewpoints, ideas, and personal qualities to the workplace [6]. Additionally, these traits have the potential to greatly benefit the business overall if managed expertly [7]. Recruitment is the first step in the process of finding and hiring potential workers from both inside and outside of a company so that they may be analysed for future employment chances; selection begins once the suitable people have been found [8]. However, the hiring and firing of employees gives the company the opportunity to present a positive image [9]. Additionally, it has been

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

proposed that in order for a business to establish and preserve a competitive advantage, it need effective personnel [10], [11].

Recruitment and selection are essential because organizations now need to hire people rapidly, in sufficient numbers, and with the correct qualities [12], [13]. Businesses usually have a clear relationship between the people they hire and how successful their operations are [14], [15]. As a result, hiring the right people is crucial to the success of the firm [10], [16]. Managers are starting to realize that employing data analytics rather than only intuition and experience to assess and manage human resources and improve employee and organizational performance may be more beneficial [17], [18].

Strengths 1.Enhanced screening effectiveness 2.Recruitment process becomes faster 3.Capability to process and interpret large datasets	Weakness 1.Algorithmic bias 2.High implementation costs 3.Concerns about data security
Opportunities 1.Broader reach to international talent 2.Better precision in selecting candidates 3.Optimization of hiring methods	Threats 1.Pushback or reluctance from applicants 2.Potential legal complications 3.Anxiety over employment displacement

Fig 1. SWOT matrix

The fields of business, society, and humanity all depend on artificial intelligence (AI). The majority of businesses are integrating AI into their company plans and strategies [19], [20], and [21].AI is improving business and technology [22], [23]. AI is enhanced by more datasets and more powerful computers [24, 25]. Routine tasks can be automated and optimized by AI to save time and money, boost productivity, make business decisions using cognitive-based technologies, prevent human mistake, anticipate user preferences, generate high-quality leads, increase revenues, and help [26], [27]. Managers understand that data analytics may be a superior tool than experience and intuition for evaluating and managing human resources as well as enhancing employee and organizational performance [28]. AI is used by human-like robots to simulate human intellect [29], [30]. Like humans, these robots are capable of seeing, hearing, making decisions, and translating languages [31].
The fields of business, society, and humanity all depend on artificial intelligence (AI). The majority of businesses are integrating AI into their company plans and strategies [19], [20], and [21].AI is improving business and technology [22], [23]. AI is enhanced by more datasets and more powerful computers [24, 25]. Routine tasks can be automated and optimized by AI to save time and money, boost productivity, make business decisions using cognitive-based technologies, prevent human mistake, anticipate user preferences, generate high-quality leads, increase revenues, and help [26], [27]. Managers understand that data analytics may be a superior tool than experience and intuition for evaluating and managing human resources as well as enhancing employee and organizational performance [28]. AI is used by human-like robots to simulate human intellect [29], [30]. Like humans, these robots are capable of seeing, hearing, making decisions, and translating languages [31],[32].
The majority of these technologies made use of algorithm analysis (AA), machine learning (ML), and natural language processing (NLP) [33].
The recruiting process may be impacted by a number of biases in human resource recruitment [34], [35], and [36]. These can happen in a number of ways, one of which is when human recruiters inadvertently give preference to candidates based on social background, gender, race, ethnicity, or handicap [37], [38]. AI could be used by businesses to develop more impartial and fair recruiting procedures [39]. The purpose of this essay is to examine how AI might help businesses create a hiring process that is more equitable, inclusive, and effective, which could ultimately benefit the business and its employees. Recent discussions [25], [29], and [38] have created new opportunities to examine how recruiters' Biased assessments and opinions can affect the employment process, despite the fact that contemporary technologies like artificial intelligence (AI) can greatly

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

enhance it. Consequently, the main goal of this research is to discuss how the use of AI can direct and neutralize the hiring process as a whole. Additionally, we illustrate the advantages and disadvantages of AI technology in hiring by creating a SWOT matrix (see Fig. 1).

II. OVERVIEW OF THEORY

A. Literature Review

Recent literature illustrates the continuous effort to comprehend and address this crucial issue as the dynamic landscape of AI and recruitment biases continues to change. The most recent research highlights the necessity of examining AI-driven hiring systems for new biases and investigating creative ways to lessen them in light of the quickening pace of technological development. As a result, the literature is summarized in Table I.

By looking at the most recent studies, approaches, and insights that influence our comprehension of how AI is changing recruiting processes and its consequences for diversity, equity, and justice, this review seeks to capture the state of the art.

It also aids in locating a gap in the body of current literature.

The analysis of the literature on how AI affects hiring biases identifies a number of important research gaps. For instance, the majority of the research either used AI from the recruiter's point of view [41], [43], [47] or noted how AI strengthened the hiring process [45], [46], [48], [49].

Furthermore, there is still a significant knowledge gap regarding the specific biases that AI faces and how they affect recruitment outcomes, particularly in China, even though studies by Horodyski [40] and Uma et al. [44] demonstrated that using AI recruitment methods can help reduce biases in the traditional hiring process.

AI integration in hiring procedures has grown in popularity as disruptive technologies continue to transform sectors and cause corporate transformation [20].

B. Development of Hypotheses

Unintentional or deliberate choices that impact the recruiting process and result in the unjust treatment of certain applicants based on characteristics such as gender, race, age, ethnicity, ability, or cultural standing are known as recruitment biases in human resources [34].

In light of technological advancements, it is necessary to take into account how AI affects human resource management, namely the recruitment and selection process [50]. We pay special attention to China for a number of reasons. First off, one of the biggest and most varied labour markets in the world is China [51]. This diversity offers a strong foundation for researching the potential effects of AI technology on the hiring process under different conditions.

Researchers can gain insight into the challenges and constraints of implementing AI technologies in a complicated labour market by examining Chinese hiring practices. Second, due to its ambitious national strategy that views AI as a component of growth, China is at the forefront of AI research and application [52].

1) **Conformity Bias**: When a recruiter ignores evidence that challenges their preconceived beliefs about a candidate and concentrates on information that confirms those beliefs, this is known as conformity bias [53]. For instance, a recruiter can believe a female candidate is uninterested in a technical field even if she possesses the necessary skills and ability. AI has the potential to lessen prejudice in a number of ways. We use a variety of informative databases that include applicants from underrepresented groups in order to develop AI algorithms.
Hypothesis 1: AI use may have a negative correlation with conformity bias.

2) **Affinity prejudice**: When a recruiter gives preference to applicants who are similar to them in terms of gender, colour, or background, this is known as affinity prejudice [54]. For instance, recruiters may feel more comfortable with a candidate who attended the same university as them, even if the other prospects have greater qualifications. AI can assess candidates based on objective standards, such project standards or competence assessments, to reduce bias. By doing this, biases that might result from assessing applications inferentially can be lessened. Thus, by employing AI to lessen affinity biases in hiring, companies may make sure they select the most qualified and varied candidates for their openings.
2) Hypothesis 2: Affinity bias may have a negative correlation with AI use.

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

3) Halo Bias: When a recruiter observes one positive trait in a prospect, they may think that all of the other traits must also be positive [55]. For instance, even in the absence of proof, a recruiter may believe that a prospect with Strong communication abilities are essential for a resume. One way to lessen bias is to use AI algorithms to evaluate applicant data and produce standardized tests that provide a more thorough and impartial picture of a candidate's abilities, background, and potential. AI can help with the planning and execution of structured interviews, which assess candidates using preset questions. AI can examine past recruiting data to identify trends and patterns that might help with decision-making.
Hypothesis 3: Halo bias may have a negative correlation with the use of AI.

4) Recency Bias: Recency bias is when a manager bases the application's final decision on the most recent occurrence, like the candidate's stellar interview, even if this does not ensure that the individual will perform well on the job after joining the organization [56]. For instance, interviewers watch for candidates' preconceived answers during the shortlisting process. Candidates are chosen for the position by interviewers depending on how they answer pre-formulated questions. We could use a variety of AI approaches to reduce these biases. AI is able to analyse text, audio, and video data from candidate interviews in order to spot patterns and highlight problems or interesting topics. By using objective data to assess candidates' responses rather than just their recollections and perceptions, this approach can assist recruiters in removing recency bias. Recruiters can examine applicants who may have missed pertinent prior experiences by using AI to match people's skills and experience with job needs.
Hypothesis 4: Recency bias may have a negative correlation with AI use.

5) Horn Bias: This phenomenon happens when one negative feature or attribute skews a person's opinion of another [57]. For example, we turn away qualified applicants because of one negative characteristic, such race or ethnicity. AI algorithms can be used to consistently assess candidates based on a set of preset standards.AI can reduce the possibility of subjective evaluation and the detrimental consequences of the horn effect by hiding crucial personal information from applicant profiles during the first screening stage of the recruiting process, including name, gender, age, and race. Race and age both lessen the possibility of subjective assessment and the detrimental consequences of the horn effect. AI can provide a more comprehensive evaluation of a candidate's fit for the role by incorporating input from a range of sources, such as peers, managers, and subordinates. AI can detect potentially biased language or tone that might be a contributing factor to the horn effect by examining the vocabulary used in job descriptions, hiring materials, and candidate profiles.
Hypothesis 5: There may be a negative correlation between horn prejudice and AI use

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

TABLE 1

Author – Year	Key Findings
Horodyski [40]	The study's findings indicate that applicants generally view AI technology positively in recruitment processes, finding it valuable and user-friendly. Notably, they recognize the most significant advantage as a substantial reduction in response time. However, applicants also identify key drawbacks, such as AI's inability to replicate nuanced human judgment, accuracy and reliability issues, and a perception of AI in recruitment as being in its early stages of development.
Horodyski [41]	AI technologies have reached a stage where they can automate substantial portions of the hiring process, consequently reshaping the roles of recruiters and HR professionals. Nonetheless, there's limited research on how recruiters perceive and adopt AI, and the factors influencing its utilization remain relatively unexplored. This study, using a web-based survey with 238 participants representing diverse demographics, examined the intentions of recruiters to incorporate AI into their workflow. By extending the Unified Theory of Acceptance and Use of Technology (UTAUT) to consider AI use frequency and education, the study uncovered significant findings.
Varsha [42]	Coded algorithms play a pivotal role in decision-making within firms, yet they can harbor various biases and uncertainties. This qualitative study underscores that the biases and vulnerabilities encountered by AI across industries have significant repercussions, leading to gender and racial biases. The study comprehensively categorizes these biases and underscores the paramount importance of responsible AI implementation in organizations to mitigate AI-related risks.
França, et al. [43]	This study offers valuable insights into the intersection of AI and Human Resource Management. To ensure the reliability of the findings, the authors conducted a systematic literature review following the PRISMA guidelines, effectively minimizing bias. The discussions center on critical themes such as AI's impact on talent management, AI bias, ethics and legal considerations, and their
	implications for HR management. Importantly, the findings stress the proactive role HR managers must play in adopting technology and bridging gaps—be they technological, human, societal, or governmental.
Uma, et al. [44]	Findings from the scoping review of the literature reveal that the incorporation of automation and analytics into the recruitment and selection processes has a significant impact. These technology-driven approaches effectively eliminate biases that are increasingly prevalent in traditional manual hiring practices. Additionally, research suggests that candidates often employ impression management tactics in traditional face-to-face interviews, but these tactics can be mitigated through automated recruitment methods.
Gupta and Mishra [45]	The examination of the current landscape reveals that while many companies have begun to incorporate AI tools into their recruitment processes, there remains untapped potential in leveraging a broader spectrum of algorithms for the entire recruitment and selection journey. This widespread adoption of AI presents both opportunities and challenges for practitioners in the realm of Human Resource Management.
Sharma, et al. [46]	The analysis indicates a steady rise in the adoption of AI technologies across HR practices. AI's role extends to various facets of HR, encompassing recruitment, selection, training, development, and resume scanning, among others. The integration of AI into HRM offers numerous advantages to organizations, including enhanced employee engagement, improved relationships, heightened competitive advantages, and optimized utilization of HR budgets. AI in HRM and delves into strategies to address these challenges, shedding light on AI's evolving role within HR practices through a comprehensive review of case studies, literature studies, and analyses of leading global organizations' AI applications in HRM.
Veglianti, et al. [47]	Recent years have witnessed a rapid expansion of technological innovations in e-recruitment systems, offering Human Resource professionals advanced tools to identify the most suitable talent for their organizations. This paper's primary objective is to investigate how AI Technologies can enhance recruitment efficiency and mitigate human errors by examining the theoretical alignments across diverse approaches and platforms designed for corporate use. The study employs a case study approach to address the research inquiries.
Aamer, et al. [48]	AI plays a pivotal role in this process, with its ultimate aim being the automation of tasks traditionally performed by humans. Remarkably swift and precise, AI operates and reacts in a manner akin to human capabilities. This study delves into the impact of AI on the Human Resource industry, with a specific focus on its application in the recruitment and selection process. The findings underscore that AI technology holds the potential to substantially enhance Human Resource and recruitment operations, offering benefits such as heightened productivity, reduced costs, enhanced accuracy, decreased workload, and an improved candidate experience.
Palos-Sánchez, et al. [49]	In organizations, the prevalence of AI is on the rise, and within the realm of Human Resource Management, AI's relevance has seen a notable surge in recent years. This article conducts a bibliometric analysis of scientific literature that systematically explores the utilization and influence of AI in HRM. The findings underscore that the application of AI in HRM is a burgeoning field marked by continuous expansion and optimistic prospects. However, it is noteworthy that the research has a distinct focus on AI's role in recruitment and selection processes, leaving other promising sub-areas relatively underexplored.

6) Contrast Bias: This phenomenon arises when two or more candidates' results differ significantly [58]. For instance, if the first applicant does exceptionally well during the interview, the subsequent decision will not be

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

advantageous for the second application. The second applicant may be rejected regardless of how well they perform in comparison to the first. By assessing candidates' competency with AI-based technologies, organizations can lessen contrast bias brought on by individual preferences or views. Chatbots with AI capabilities and automated interviews can streamline the hiring procedure and guarantee that every applicant is asked the same questions. Based on the preferences or viewpoints of interview subjects, this method helps eliminate insider bias.
Hypothesis 6: The use of AI may have a negative correlation with contrast bias.

7) Overall Recruitment Biasness: By utilizing effective and efficient AI techniques, organizations can lessen the aforementioned biases. In order to lessen unconscious bias in the hiring process, we employ machine learning algorithms to evaluate resumes, job titles, and other hiring data. AI is also able to examine job descriptions and spot any wording that can be exclusionary or discriminatory, such sexist phrases or language that highlights traits exclusive to certain groups. AI has the ability to create customized pre-employment exams that evaluate a candidate's aptitudes and competencies independently of subjective assessments.
Hypothesis 7: The use of AI may have a negative correlation with general prejudice in hiring

III. METHODOLOGY

A. Population, Data, Sample.

This study aims to examine how biases in the hiring process are affected by the use of AI. This study focuses on Chinese workers in the manufacturing industry in order to accomplish the stated goal. This industry was chosen because it is well-known in China, where it employs the majority of the labour force. By focusing on this industry, it is certain that a sizable percentage of the working population has been reached. Our method is based on a questionnaire to collect the statistical data. Chinese, the official language and one that most Chinese employees can understand, is used to develop the questionnaire. Making this choice is crucial to ensuring that the participants fully understand the questions, which eventually leads to more accurate and perceptive responses. The questionnaire is also distributed with a cover note explaining the study's objectives. This letter achieves a number of objectives. It initially ensures that participants are aware of the objectives of the study. Second, it motivates participants to provide thoughtful and truthful responses.
Due to a number of numerical data difficulties regarding the quality, the study also takes some precautions to reduce any prejudices [59]. Respondents, for instance, are guaranteed total confidentiality. Furthermore, the survey encourages respondents to answer honestly by letting them know that there are no right or incorrect responses. We employ stratified random sampling approaches based on the study's nature. By concentrating on the manufacturing sector, the population is further reduced, management is made simpler, and dependability is guaranteed. Similar to this, this study guarantees diversity in the manufacturing industry with regard to employment titles, experience levels, and geographic regions, offering a thorough grasp of how the use of AI technologies can affect prejudices in hiring [60], [61]. 423 of the 650 questionnaires that were sent out to gather data were answered, yielding a response rate of almost 65%.

B. Variables Measurement

The creation of dependent, independent, and control variables, as well as their measuring scales and supporting literature, are explained in Table II. In particular, our research focuses on recruitment biases and divides them into seven different categories. Likewise, AI is the study's independent variable. Since artificial intelligence is a technology and cannot be directly assessed with survey tools, we quantify AI using two approximations. The first stand-in is the application of AI tools, which illustrates how AI is used in the industrial industry, especially when hiring staff. Fairness in the application of AI tools serves as the second proxy for measuring AI. The effectiveness of applying AI tools is measured by the aforementioned proxy. Lastly, the study's control variables are corporate-level demographics.

C. Variables Measurement

To identify the empirical model and assess the extent to which AI use impacts recruiting biases, we employ parametric analysis. In other words, we employ certain statistical techniques to observe the effects of independent and control variables on dependent variables. For a number of reasons, parametric analysis is usually preferred for survey datasets. First, parametric tests, like multivariate regressions, are useful for

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

determining the impact because they are statistically significant. The second benefit of parametric analysis is that it yields results that are easy to understand and interpret. Third, a wide range of variables that are frequently found in survey datasets can be handled with parametric analysis. Specifically, we created the empirical model that follows, which backs up our empirical research and hypothesis testing.

$$\text{Recruitment Bias}_i = \beta_0 + \beta_1 \text{ Usage of AI Tools}_i + \sum_{k=1}^{6} \beta_k \text{ Control Variables} + €_i$$

Recruitment biases, which are further divided into conformity, affinity, halo, recency, horn, contrast, and overall recruitment biases, are the dependent variable in the aforementioned equation, which reflects regression models. Additionally, the use of AI tools is an independent variable. Lastly, control variables are divided into ownership structure, legal status, and business size. The expected value of Recruitment Biasesi for all independent and control factors are zero is represented by the intercept term β0. The discrepancy between the observed and model-predicted values of Recruitment Biasesi is represented by the error term εi. It captures the impact of random variation and unseen factors.

IV. EMPIRICAL ANALYSIS

The sample of the study consists of 423 respondents from China(N=423). Table III provides detailed descriptive statistics about the respondents. According to the respondents' provided information, 30% work in domestic-owned firms, 38% in foreign firms, and 32% in foreign and government-owned firms, respectively. According to their legal status, 40% of respondents work in sole proprietorship firms, 16% in partnership firms, and 44% in companies. Whereas 24% of respondents are working in small firms, 28% are in medium-sized firms, and 48% are in companies.

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

TABLE II Variable Definitions

Variables Name	Measurement	Scale	Supportive Literature
Dependent Variables			
	The interviewers seemed to expect candidates to conform to a specific set of beliefs or behaviors.	5-Point Likert Scale – (1-5 Strongly Agree-Strongly Disagree) Higher value represents lesser biasness	Liu, et al. [53]
	Interviewers showed a preference for candidates with similar backgrounds or interests as themselves.	5-Point Likert Scale – (1-5 Strongly Agree-Strongly Disagree) Higher value represents lesser biasness	Contreras, et al. [54]
	Positive attributes or qualifications of some candidates overshadowed other aspects of their candidacy.	5-Point Likert Scale – (1-5 Strongly Agree-Strongly Disagree) Higher value represents lesser biasness	Schmidt, et al. [55]
	The interview questions focused primarily on my most recent job or experience, neglecting my earlier achievements or experiences.	5-Point Likert Scale – (1-5 Strongly Agree-Strongly Disagree) Higher value represents lesser biasness	Cakici and Zaremba [56]
	A single mistake or shortcoming in my application or interview seemed to overshadow my other qualifications.	5-Point Likert Scale – (1-5 Strongly Agree-Strongly Disagree) Higher value represents lesser biasness	Rowley, et al. [57]
		5-Point Likert Scale – (1-5 Strongly Agree-Strongly Disagree) Higher value represents lesser biasness	
		5-Point Likert Scale – (1-5 Strongly Agree-Strongly Disagree) Higher value represents lesser biasness	Thomas and Reimann [34]
Independent Variable			
	AI tools, such as resume screening algorithms, were used in my recruitment process.	5-Point Likert Scale – (1-5 Strongly Disagree-Strongly Agree) Higher value represents higher usage of AI tools	Trivedi [31]
Fairness in the Usage of AI Tools	I believe AI tools were used fairly and without bias in my recruitment process.	5-Point Likert Scale – (1-5 Strongly Disagree-Strongly Agree) Higher value represents fairness in the usage of AI tools	
Control Variables			
		Dummy variable, value is "1" if firm has number of employees from 5 to 19, and "0" otherwise.	
		Dummy variable, value is "1" if firm has number of employees from 20 to 99, and "0" otherwise.	
		Dummy variable, value is "1" if firm has number of employees more then 100, and "0" otherwise.	
		Dummy variable, value is "1" if firm is sole proprietorship, and "0" otherwise.	
		Dummy variable, value is "1" if firm is partnership, and "0" otherwise.	
		Dummy variable, value is "1" if firm is company, and "0" otherwise.	
		Dummy variable, value is "1" if owned by domestic individual, companies or organizations, and "0" otherwise.	
		Dummy variable, value is "1" if owned by government or state, and "0" otherwise.	
		Dummy variable, value is "1" if owned by foreign individuals, companies or organizations, and "0" otherwise.	

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

TABLE III Descriptive Statistics

Variables	Obser vation	Mean	Standard Deviation	Minimum	Maximum	Skewness	Kurtosis
Use of AI Tools	423	2.74	1.06	1	5	0.01	-0.47
Fairness in Use of AI Tools	423	2.88	0.97	1	5	-0.21	-0.06
Conformity Bias	423	2.12	0.62	1	5	-0.18	-0.35
Affinity Bias	423	2.28	0.92	1	5	0.25	-0.55
Halo Bias	423	2.4	0.78	1	5	0.06	-0.64
Recency Bias	423	2.44	1.04	1	5	0.01	-0.36
Horn Bias	423	2.4	0.9	1	4	-0.03	-0.53
Contrast Bias	423	2.54	1.15	1	5	0.18	-0.23
Recruitment Process Biasness	423	2.76	1.12	1	5	-0.08	-0.42
Domestic Owned firms	423	0.3	0.47	1	1	0.6	-1.51
Foreign Owned Firms	423	0.38	0.47	0	1	0.23	-1.85
Government Owned Firms	423	0.32	0.47	0	1	0.47	-1.67
Solo Proprietorship Firms	423	0.4	0.49	0	1	-0.13	-1.49
Partnership Firms	423	0.16	0.37	0	1	1.20	0.46
Company	423	0.44	0.49	0	1	-0.05	-1.84
Small Size Firms	423	0.24	0.5	0	1	0.97	0.32
Large Size Firms	423	0.48	0.43	0	1	-0.48	-1.39

Most variables have skewness values close to 0, indicating approximately symmetric distributions. A few variables have slightly right-skewed (positive skewness) or left-skewed (negative skewness) distributions, but the skewness values are relatively small. Many variables have negative kurtosis values, indicating platykurtic distributions (light tails). However, the kurtosis values are close to 0, suggesting approximately normal distributions for most variables. A few variables have moderately negative kurtosis values, indicating platykurtic distributions, and a few have moderately positive kurtosis values, indicating leptokurtic distributions (heavy tails). Regarding the validity of empirical analysis, we have adopted both internal and external validation. To internally validate the findings of the study, we have incorporated the Cornbrash alpha technique. The said test is an important measure to check the reliability and validity of empirical data and show how close the set of items is to the group. It is also considered a factor to check the reliability of the scale. In empirical analysis, a high alpha value represents higher consistency and validity of the construct. It also specifies that the items used are suitable together on a cohesive scale. According to the findings of the said test reported in Table IV, the variables of this study are not only reliable to use but also consistent to incorporate in empirical analysis. All the alpha values exceed the threshold of 0.7, suggesting a heightened level of internal consistency and validity. The total scale value exceeds 0.7, so ensuring a substantial level of overall reliability. Furthermore, the correlation matrix also helps to understand the extent to which the measures accurately reflect differences between different constructs, thus significantly contributing to the overall validity assessment. Another reason to use correlation analysis is to ensure that the variables used in this study are free from any multicollinearity issues. According to the correlation results reported in Table V, the constructs are valid and the variables are free from multicollinearity issues. These results validate the accuracy of the data and variables. Based on the reported results no correlation coefficient is beyond 0.8, thus the presence of autocorrelation is ruled out. Multivariate regression is applied to explore the impact of AI on recruitment biases. The results revealed that AI has a positive relationship with all types of 0.01), halo bias ($\beta = 0.162$, $t = 4.70$, $p < 0.01$), recency bias ($\beta = 0.273$, $t = 6.13$, $p < 0.01$), horn bias ($\beta = 0.154$, $t = 3.86$, $p < 0.01$), contrast bias ($\beta = 0.117$, $t = 2.26$, $p < 0.01$), and

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

recruitment process biases (β = 0.011, t = 2.62, p < 0.05). So, these results prove that AI tools can significantly reduce recruitment biases, as given in Table VI.

TABLE IV Reliability Test

Items	Observation	Average Interitem Correlation	Alpha
Use of AI Tools	423	0.09	0.74
Fairness in Use of AI Tools	423	0.09	0.73
Conformity Bias	423	0.09	0.73
Affinity Bias	423	0.10	0.76
Halo Bias	423	0.09	0.72
Recency Bias	423	0.09	0.73
Horn Bias	423	0.12	0.79
Contrast Bias	423	0.11	0.77
Recruitment Process Biasness	423	0.10	0.76
Domestic Owned Firms	423	0.09	0.74
Foreign Owned Firms	423	0.11	0.78
Government Owned Firms	423	0.10	0.76
Solo Proprietorship	423	0.09	0.74
Partnership Firms	423	0.11	0.77
Company	423	0.10	0.76
Small Size Firms	423	0.11	0.78
Medium Size Firms	423	0.10	0.75
Large Size Firms	423	0.11	0.78
Test Scale		**0.10**	**0.77**

TABLE V Correlation Matrix

2	0.50^{a}													
3	0.08^{c}	0.45												
4	0.28^{a}	0.15	0.29											
5	0.27	0.41	0.69^{a}	0.32^{c}										
6	0.30^{c}	0.41^{a}	0.20	0.06	0.43^{a}									
7	0.20	0.08	–0.19^{a}	0.06^{a}	0.03^{c}	0.13								
8	0.13^{a}	0.25^{a}	–0.09	–0.22	0.09	0.65^{a}	0.26							
9	0.00^{b}	0.43	0.39^{a}	–0.32	0.29^{c}	0.33^{b}	–0.06	0.21^{b}						
10	0.18^{a}	0.00	0.13	0.10	0.09^{a}	0.01	0.19^{b}	0.00	0.13^{a}					
11	0.01^{c}	0.06^{a}	0.07	0.02	0.10^{a}	0.13^{b}	0.23	0.05^{a}	0.06^{a}	-0.49^{a}				
12	0.26^{a}	0.00	0.09^{c}	0.28^{c}	0.06^{a}	0.03	0.05^{a}	0.02^{b}	0.05	0.11^{b}	-0.16			
13	0.06^{a}	0.02	0.03^{a}	0.04^{c}	0.14	0.15^{a}	0.11^{a}	0.05	0.11^{a}	–0.20^{a}	0.60^{b}	–0.37^{c}		
14	0.24^{b}	0.16^{a}	0.04	0.08	0.13^{c}	0.25^{a}	0.11	0.28^{a}	0.21^{a}	0.00	0.02^{a}	–0.13^{a}	0.05^{a}	
15	0.14^{b}	0.07	0.04^{c}	0.24	0.07	0.06	0.06^{b}	0.06^{b}	0.09^{c}	0.04^{b}	–0.11	0.27^{a}	–0.10^{b}	–0.33^{a}

All the regression models have statistically significant F- statistics values, indicating that they are neither mis-specified nor provide misleading or weak results. As far as the empirical models' R-squares and adjusted R-squares are concerned, they show low statistical values. In cross-sectional survey datasets with 423 observations, it's common to observe a low value of R-Square. Several factors contribute to this phenomenon. First, numerous complex and often unobserved factors influence human behaviour and are often the focus of

IJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

surveys, making it challenging to fully explain the variables included in the model. Additionally, survey data frequently contain measurement errors, further reducing the ability of the independent variables to fully explain the variation in the dependent variable. Second, the population heterogeneity in cross-sectional data means that finding a single model that accurately predicts the dependent variable for all individuals is challenging.

TABLE VI Regression Analysis (Main Results)

Multivariate Regression Models
Unit of Observation-Cross Section
Dependent Variable-Recruitment Biases

	Conformity	**Affinity**	**Halo**	**Recency**	**Horn**	**Contrast**	**Recruitment Process**
Independent Variable Use of AI Tools	0.004*** (3.06)	0.176*** (4.46)	0.162*** **(4.70)**	0.273*** (6.13)	0.154*** (3.86)	0.117*** (2.26)	0.011** (2.62)
Control Variables Foreign Owned Firms	0.292*** (4.26)	0.195*** (2.05)	0.195*** (2.35)	0.001*** (3.01)	0.111** (2.16)	0.109** (1.90)	0.465*** (3.81)
Government Owned Firms	-0.276*** (-3.30)	-0.263** (-2.26)	-0.178* (-1.75)	-0.162 (-1.24)	- 0.414*** (-3.53)	-0.133*** (-2.88)	-0.279* (-1.87)
Partnership Firms	0.140* (1.62)	0.474*** (3.93)	0.045 (0.43)	0.165 (1.22)	0.116 (0.96)	0.303** (1.92)	0.014*** (2.09)
Company	0.020** (1.95)	0.046*** (2.44)	0.153* (1.67)	0.133*** (2.13)	0.015*** (3.14)	0.127*** (2.93)	0.149*** (2.11)
Medium Size Firms	0.034*** (2.51)	0.111 (1.18)	0.124 (1.52)	0.581*** (5.49)	0.144 (1.52)	0.709*** (5.78)	0.513*** (4.26)
Large Size Firms	0.033 (2.47)	0.395*** (4.07)	0.053 (3.62)	0.360*** (3.29)	0.003*** (4.03)	0.072*** (3.57)	0.030* (1.74)
Constant	1.906*** (21.39)	1.467*** (11.85)	1.782*** (16.49)	1.847*** (13,.21)	2.124*** (16.98)	2.604*** (16.08)	2.296*** (14.45)
Model Summary Number of Observations	423	423	423	423	423	423	423
F-Sat	4.06	13.81	8.46	14.84	7.98	7.31	6.30
Prob.>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.055	0.164	0.108	0.174	0.102	0.094	0.082

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

TABLE VII
Regression Analysis (Robust Check)
Multivariate Regression Models
Unit of Observation-Cross Section
Dependent Variable-Recruitment Biases

	Conformity	**Affinity**	**Halo**	**Recency**	**Horn**	**Contrast**	**Recruitment Process**
Independent Variable Fairness in Use of AI Tools	0.288*** (11.39)	0.127*** (3.18)	0.027* (1.76)	0.400*** (9.37)	0.069* (1.72)	0.260*** (5.14)	0.545*** (12.26)
Control Variables Foreign Owned Firms	0.267*** (4.46)	0.263*** (2.79)	0.302 (7.96)	0.086* (0.85)	0.175* (1.83)	0.081*** (2.67)	0.419*** (3.99)
Government Owned Firms	-0.212*** (-2.84)	0.255*** (-2.17)	-0.012 (-0.15)	0.104*** (-2.83)	0.412*** (-3.46)	0.178*** (-2.20)	-0.158*** (-3.21)
Partnership Firms	0.168** (2.27)	0.629*** (5.37)	0.210** (2.08)	0.093 (0.74)	0.016 (0.13)	0.184*** (2.24)	0.042*** (3.32)
Company	0.002*** (3.03)	0.031*** (2.27)	0.268*** (3.11)	0.268*** (2.40)	0.079*** (2.75)	0.064*** (2.48)	0.191*** (1.64)
Medium Size Firms	0.063 (1.07)	0.065 (0.69)	0.088 (1.14)	0.583 (5.84)	0.198 (2.10)	0.679 (5.73)	0.695 (6.68)
Large Size Firms	0.012*** (2.19)	0.389*** (3.96)	0.026*** (2.32)	0.386*** (3.68)	0.001*** (2.01)	0.089*** (2.72)	0.070*** (3.64)
Constant	1.083*** (12.10)	1.519*** (10.76)	1.332*** (11.26)	1.342*** (8.89)	2.290*** (16.01)	2.130*** (11.89)	0.748*** (4.76)
Model Summary Number of Observations	423	423	423	423	423	423	423
F-Stat	23.66	12.20	17.63	22.91	6.14	10.63	29.70
Prob.>	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R^2	0.252	0.148	0.201	0.246	0.080	**0.**131	0.297

*p<0.1, **p<0.05, ***p<0.01, t statistics in parentheses

V.RESULTS AND DISCUSSION

By reducing biases that historically hamper recruiting decisions, AI has the potential to make a big impact on the recruitment process [65]. Although AI is not a magic bullet, it has many benefits that make hiring fairer and more objective [50]. AI's capacity for blind screening is a critical factor. Reviewing resumes and applications that include personal identifiers like names, photographs, or addresses is a common step in the traditional hiring process [35]. These identifiers may cause recruiters to have unconscious prejudices, potentially disqualifying qualified applicants. AI technologies can remove this information, ensuring that the initial screening solely focuses on credentials and abilities. As a result, there may be less discrimination against candidates based on their gender, ethnicity, or socioeconomic position [66], [67]. Some of the prejudices that frequently seep into the recruiting process are confirmation bias, affinity bias, and cultural bias [68]. AI systems, appropriately created and trained, can reduce these biases by focusing on the data and predetermined criteria [35]. They can find patterns of successful hires based on objective criteria by analysing enormous databases [69].

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

TABLE VIII Summary of Findings

Recruitment Biases	Hypotheses	AI Tools Usage	
		Usage	**Fairness**
Conformity Bias	H_1	Proved	Proved
Affinity Bias	H_2	Proved	Proved
Halo Bias	H_3	Proved	Proved
Recency Bias	H_4	Proved	Proved
Horn Bias	H_5	Proved	Proved
Contrast Bias	H_6	Proved	Proved
Overall Recruitment Process			
Biasness	H_7	Proved	Proved

VI.CONCLUSIONS AND FUTURE WORK

From personal assistants like Siri and Alexa to self-driving cars, medical diagnosis, and financial analysis, AI has already started to change our lives in a variety of ways [70]. The relationship between AI and life remains complex and constantly evolving. It is crucial to continuously monitor and assess how AI affects our daily lives to ensure its use benefits humanity and safeguards our values and interests [71]. The field of AI, which is currently in a state of rapid development, focuses on developing devices and computer programmers that are capable of carrying out operations that typically require human intelligence, such as perception, reasoning, learning, and decision-making [72]. HR departments can use AI to improve decision-making, streamline processes, and improve employee experiences [73]. AI technologies have the potential to increase hiring uniformity, objectivity, and efficiency, which would have significant policy ramifications. Legislators must establish a robust legislative framework to ensure impartiality and an AI-powered hiring process. This paradigm should prioritize responsibility, transparency, and equity while being flexible enough to adjust to the rapidly evolving AI environment. By establishing clear guidelines and standards, policymakers can encourage businesses to employ AI in hiring in an ethical manner. Policy measures like thorough algorithmic auditing are also necessary. To find and address any biases, recruitment AI systems must undergo routine audits. By increasing openness and trust, independent auditors can reassure job searchers that their applications are equitable.

Education and training should be given priority in policy matters as well. Legislators will fund training for AI engineers, hiring managers, and HR specialists. Professionals could benefit from these seminars by learning about AI bias, its impacts, and ways to lessen it. Policymakers can assist workers in making informed AI hiring decisions by funding education. Priorities for legislation should also include data collection and transparency in AI-driven hiring. It is crucial to support businesses in disclosing AI tool data and regularly examining data sources for biases. Robust regulations ought to guarantee that data are impartial and representative, encouraging openness and confidence among job searchers utilizing AI-powered hiring platforms. Additionally, by combining these AI systems with incentive programs, we may efficiently compensate those who work harder and end up earning more money, or the other way around.

It is crucial to take into account certain limitations even though our study provided valuable insights on AI's potential to lessen hiring prejudices. First, our findings may not be generalizable to other contexts or demographics due to the narrow sample size and the particular industry in which we performed our study. Future research should try to replicate our study in different industries and with more diverse populations in order to evaluate the generalizability of our findings. Second, the data used in our study was self-reported by participants, which may have biases or errors. Future studies could incorporate other methods like behavioral observation or objective performance measurements to give a more complete evaluation of how AI reduces biases in hiring.

Future research on employing AI tools to reduce recruiting biases should explore novel approaches to make AI algorithms more transparent and interpretable, helping job seekers and hiring organizations comprehend the decision-making process. AI recruitment systems require more advanced continuous monitoring and real-time bias detection methods to develop adaptive models that can self-correct and adjust to shifting biases. Researchers should also investigate how AI might minimize prejudices and actively promote diverse and inclusive work-places. We should prioritize standardized, independent auditing mechanisms for recruitment AI algorithms to

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

evaluate fairness and accountability. We must explore AI in hiring within ethical and legal frameworks to comply with data privacy, anti- discrimination, and individual rights laws. Fair, honest, and ethical AI-driven recruitment practices will depend on these future research directions.

VII.REFERENCES

[1] In China's Opportunities for Development in an Era of Great Global Change, S. Cheng discusses the future growth of companies in the intelligent world while riding the latest technological wave. Springer, Berlin, Germany, 2023, pp. 203–213.
[2] “Knowledge sharing and innovation performance: A case study on the impact of organizational culture, structural capital, human resource management practices, and relational capital of real estate agents,” Humanities Social Sci. Commun., vol. 10, no. 1, pp. 1–16, 2023, C.-C. Lee, W.-C. Yeh, Z. Yu, and Y.-C. Luo.
[3] "Mediating role of entrepreneurial work-related strains and work engagement among job demand–resource relationships," by Q. Wang, S. N. Khan, M. Sajjad, I. H. Sarki, and M. N. Yaseen
[4] Int. J. Innov. Res. Sci. Stud., vol. 6, no. 3, pp. 682–693, 2023, J. M. Martins, S. S. H. Shah, A. Abreu, S. Sattar, and S. Naseem, "The impact of system dynamic employee recruitment process on organizational effectiveness."
[5]In Thunderbird International Business Review, vol. 65, no. 1, pp. 161–175, 2023, S. Showkat, T. Wani, and J. Kaur discuss the "new normal" consequences for global talent in the aftermath of economic nationalism and recession.
[6]In 2023, S. Chatterjee, R. Chaudhuri, D. Vrontis, R. V. Mahto, and S. Kraus published "Global talent management by multinational enterprises post-COVID-19: The role of enterprise social networking and senior leadership" in Thunderbird International Business Review, vol. 65, no. 1, pp. 77–88.
[7] "Business ethics," by J. N. N. Ugoani, in The Palgrave Handbook of Global Sustainability. Springer, Berlin, Germany, 2023, pp. 1763–1782.
[8] Inverge J. Social Sci., vol. 2, no. 2, pp. 146–164, 2023; M. H. Khan, "The role of recruitment and selection on organizational performance: An empirical investigation into the impact of recruitment and selection on organizational performance."
[9] "Instrumental variables estimation: Assumptions, pitfalls, and guidelines," Leadership Quarterly, vol. 34, 2023, Art. no. 101673, N. Bastardoz, M. J. Matthews, G. B. Sajons, T. Ransom, T. K. Kelemen, and S. H. Matthews.
[10] Int. J. Artif. Intell. Res., vol. 6, no. 1.1, pp. 1–6, 2023; H. S. Hadijah, "Implementation of talent management as a strategy for achieving company competitive advantage."
[11] A. Shahzad, N. Zahrullail, A. Akbar, H. Mohelska, and A. Hussain, J. Risk Financial Management, vol. 15, no. 10, 2022, Art. no. 428, "COVID-19's impact on fintech adoption: Behavioral intention to use the financial portal."
Int. J. Hum. Capital Urban Manage, vol. 8, no. 2, pp. 229–244, 2023; A. Santos, "Human resource lens: Perceived performances of ISO 9001: 2015 certified service firms”.
[13] Mer and Virdi, A. Mer and A. S., "A post-pandemic perspective on navigating the paradigm shift in HRM practices through the lens of artificial intelligence," in The Adoption and Effect of Artificial Intelligence in Human Resource Management, Part A. Bingley, U.K.: Emerald Publishing Limited, 2023, pp. 123-135.
[14] "A thorough analysis of the impact of digital technology on human resource management," Technol., Manage. Bus., vol. 31, pp. 7–19, 2023, by A. Shukla, L. Mishra, and A. Agnihotri.
[15] M. Coccia, "Incentives to support public organizations' performance and motivation," J. Econ. Bibliogr., vol. 6, no. 1, pp. 20–29, 2019.
[16] N. Wen, M. Usman, and A. Akbar, "The relationship among corporate innovation, institutional effectiveness, and managerial overconfidence," Sustainability, vol. 15, no. 8, 2023, Art. no. 6524.
[17] "Personalized human resource management via HR analytics and artificial intelligence: Theory and implications," by X. Huang, F. Yang, J. Zheng, C. Feng, and L. Zhang pp. 598–610, Asia Pac. Manage. Rev., vol. 28, 2023.
[18] Global Encyclopedia of Public Administration, Public Policy, and Governance, "Comparative incentive systems," by M. Coccia Volume 10 of Springer International Publishing AG, a division of Springer Nature. Springer, Berlin, Germany, 2019.
[19] "Data-driven artificial intelligence (AI) models in the workforce development planning," in Designing

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

Workforce Management Systems for Industry 4.0, by P. Jain, V. Tripathi, R. Malladi, and A. Khang. CRC Press, Boca Raton, FL, USA, 2023, pp. 159–176.
[20] M. Coccia, "Industrial transformation: sources of disruptive technologies," L'industria, vol. 38, no. 1, pp. 97–120, 2017.
[21] "Application of grey relational analysis for utilizing artificial intelligence methods in aviation management," in AI in Business: Opportunities and Limitations: Volume 1, by B. Ivan, B. Olga, H. Oksana, P. Roman, S. Marta, and K. Khrystyna. Springer, Berlin, Germany, 2024, pp. 113–123.
[22] H. O. Khogali and S. Mekid, "Some long-term societal and ethical impact features of the blended future of automation and AI," Technol. Soc., vol. 73, 2023, Art. no. 102232.
[23] In the Global Encyclopedia of Public Administration, Public Policy, and Governance, volume 10, M. Coccia discusses "Destructive technologies for industrial and corporate change." Springer, Berlin, Germany, 2020, Art. no. 978-3.
In Amer. J. Artif. Intell., vol. 7, no. 1, 2023, Art. no. 24, J. P. Bharadiya compares artificial intelligence and business intelligence using Big Data analytics.
[25] "Artificial intelligence in employee recruitment," Glob. Bus. Organizational Excellence, vol. 43, pp. 56–66, 2024, by Y. S. BalciogΘlu and M. Artar.
[26] "Exploring the impact of artificial intelligence in business decision making," by S. F. A. Ahmed, S. H. Krishna, K. Ganeshkumar, U. Anthiyur, and R. Manivel, in J. Data Acquisition Process, vol. 38, no. 3, 2023, Art. no. 686.
Technol. Anal. Strategic Manage., vol. 29, no. 9, pp. 1048–1061, 2017;
[27] M. Coccia, "Sources of technological innovation: Radical and incremental innovation problem-driven to support competitive advantage of firms."
[28] P. M. Madhani, "Compensation Benefits Rev., vol. 55, no. 1, pp. 31–45, 2023: Using human resources analytics to improve business performance."
[29] "Will AI in human resources create a digital Frankenstein?" by K. M. Lukaszewski and D. L. Stone, Organizational Dyn., vol. 53, 2024, Art. no. 101033.
[30] "Designing recruitment programs for impact," by W. F. Cascio and K. Ehrhardt, in Essentials of Employee recruiting. Routledge, 2024, pp. 330–350, Evanston, IL, USA.
[31] Microsoft Azure AI Fundamentals Certification Companion: How to Get Ready for the AI-900 Exam, by K. S. Trivedi, "Fundamentals of artificial intelligence." Springer, Berlin, Germany, 2023, pp. 11–31.
[32] "The effect of artificial intelligence on human resources practices in the United Arab Emirates," Humanities Social Science Communication, vol. 8, no. 1, pp. 1–9, 2021, by A. Singh and A. Shaurya.
[33] Korea Pac. Bus. Rev., pp. 1–20, April 2024; J. Kim, S. Battaglia, and H. H. Kim, "Collaborative intelligence achieved from AI-enabled recruitment: A case study of POSCO in South Korea."
[34] O. Thomas and O. Reimann, "The bias blind spot among HR employees in hiring decisions," German J. Hum. Resource Manage, vol. 37, no. 1, pp. 5–22, 2023.
[35] Z. Chen, "Discrimination and ethics in AI-enabled hiring procedures," Humanities Social Science Communication, vol. 10, no. 1, pp. 1–12, 2023.
[36] "Fairness, AI & recruitment," Comput. Law Secur. Rev., vol. 53, 2024, Art. C. Rigotti and E. Fosch-Villaronga.
Algorithmic fairness, by Das, R. Stanton, and N. Wallace, Annu. Rev. Financial Econ., vol. 15, pp. 565–593, 2023 [37].
[38] "Impact of AI-focused technologies on social and technical competencies for HR S managers–A systematic review and research agenda," by R. Deepa, S. Sekar, A. Malik, J. Kumar, and R. Attri, Technological Forecasting Social Change, vol. 202, 2024, Art. no. 123301.
[39] G. Kiradoo, "Unlocking the potential of AI in business: Challenges and ethical considerations," Recent Publications in Science and Technology, vol. 6, pp. 205–220, 2023.
[40] P. Horodyski, "How do applicants perceive AI in the hiring process?" Comput. Hum. Behav. Rep., vol. 11, 2023, Art. no. 100303.
[41] P. Horodyski, "Human resources based on artificial intelligence (AI) as perceived by recruiters," Art. no. 100298 in Comput. Hum. Behav. Rep., vol. 10, 2023.
[42] P. Varsha, "A systematic literature review on managing biases in artificial intelligence systems," Int. J. Inf. Manage. Data Insights, vol. 3, no. 1, 2023, Art. no. 100165.

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

[43] "Artificial intelligence applied to potential assessment and talent identification in an organizational context," Heliyon, vol. 9, no. 4, 2023, Art. no. e14694, T. J. F. França, H. São Mamede, J. M. P. Barroso, and V. M. P. D. Dos Santos.
[44] Bingley, U.K.: Emerald Publishing Limited, 2023, pp. 155–174. V. Uma, I. Velchamy, and D. Upadhyay, "Recruitment analytics: Hiring in the era of artificial intelligence," in The Adoption and Effect of Artificial Intelligence on Human Resources Management, Part A.
[45] In The Adoption and Effect of Artificial Intelligence on Human Resources Management, Part B. Bingley, U.K.: Emerald Publishing Limited, 2023, pp. 1–11, A. Gupta and M. Mishra discuss artificial intelligence for recruiting and selection.
[46] In The Adoption and Effect of Artificial Intelligence on Human Resources Management, Part B. Bingley, U.K.: Emerald Publishing Limited, 2023, pp. 111–126, A. Sharma, D. Sharma, and R. Bansal discuss the difficulties in implementing AI in HRM practices.
[47] In Smart Technologies for Organizations: Managing a Sustainable and Inclusive Digital Transformation, E. Veglianti, M. Trombin, R. Pinna, and M. De Marco discuss whether customized AI may be used to recruit talent without bias. Springer, Berlin, Germany, 2023, pp. 245–261.
[48] In Proc. Int. Conf. Bus. Technol., 2023, pp. 622–630, A. K. A. Aamer, A. Hamdan, and Z. Abusaq discuss the effects of AI on the human resources sector and the hiring and selection process.
[49] "Artificial intelligence and human resources management: A bibliometric analysis," Appl. Artif. Intell., vol. 36, no. 1, 2023, Art. no. 2145631, P. R. Palos-Sánchez, P. Baena-Luna, A. Badicu, and J. Infante-Moro.
[50] P. Budhwar et al., "Perspectives and research directions on ChatGPT in the era of generative artificial intelligence," Hum. Resource Manage. J., vol. 33, pp. 606–659, 2023.
[51] C. K. Lee, Two Worlds of Factory Women: Gender and the South China Miracle. University of California Press, Berkeley, CA, USA, 2023.

[52] E. Racine, "China's AI-powered surveillance state after COVID: Wide-ranging ramifications," Surveill. Soc., vol. 21, no. 3, pp. 269–275, 2023.
[53] "Disentangling interest and conformity for eliminating popularity bias in session-based recommendation," Knowing Inf. Syst., vol. 65, no. 6, pp. 2645–2664, 2023, by Q. Liu, F. Tian, Q. Zheng, and Q. Wang.
[54] "Executive women's networks: The affinity bias of social capital," Acad. Manage. Proc., vol. 2023, no. 1, 2023, Art. no. 15943, M. G. Contreras, R. Mateos De Cabo, and R. Gimeno.
[55] Halo effects in grading: An experimental method, by F. T. Schmidt, A. Kaiser, and J. Retelsdorf, Educ. Psychol., vol. 43, no. 2/3, pp. 246–262, 2023.
[56] "Recency bias and the cross-section of international stock returns," by N. Cakici and A. Zaremba, Journal of International Financial Markets, Institutions Money, vol. 84, 2023, Art. no. 101738.
[57] "Horns effect," in Encyclopedia of Human Resource Management, by C. Rowley, N. Ramasamy, and A. Cox. Edward Elgar Publishing, Bingley, U.K., 2023, pp. 172–173.
[58] "Talent management errors in recruiting-case study approach," by M. Salimi and K. Chandrasekar, i-Manager's J. Manage, vol. 17, no. 4, 2023, Art. no. 22.
[59] "Numerical data quality in IS research and the implications for replication," Decis. Support Syst., vol. 115, pp. A1–A7, 2018, by J. R. Marsden and D. E. Pingry.
[60] Organizational Res. Methods, vol. 9, no. 2, pp. 221–232, 2006; P. E. Spector, "Method variance in organizational research: Truth or urban legend?
[61] "Artificial intelligence in education: A review," by L. Chen, P. Chen, and Z. Lin, IEEE Access, vol. 8, pp. 75264–75278, 2020.
[62] Int. J. Entrepreneurial Behavior Res., vol. 29, no. 6, pp. 1248–1268, 2023, K. A. Wickstrøm and T. E. Bager, "The influence of the propensity of small-firm managers to enroll in training programs on subsequent training outcome."
[63] Z. Chen, "Recruiters and AI Working Together: Reducing Human Prejudices in the Workplace," Cogn., Technol. Work, vol. 25, no. 1, pp. 135–149, 2023.
[64] "Managerial duties and managerial biases," by U. Malmendier, V. Pezone, and H. Zheng, Manage. Sci., vol. 69, no. 6, pp. 3174–3201, 2023.
[65] "AI for hiring in context: A perspective on overcoming the unique challenges of employment research to

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

mitigate disparate impact," by S. Kassir, L. Baker, J. Dolphin, and F. Polli, AI Ethics, vol. 3, no. 3, pp. 845–868, 2023.
[66] In Feminist AI: Critical Perspectives on Algorithms, Data, Intelligent Machines, J. Wajcman and E. Young discuss how feminism challenges artificial intelligence. Oxford University Press, Oxford, U.K., 2023.
[67] "Right person for the right job: The impact of top management's occupational background on Chinese enterprises' R&D efficiency," Econ. Res., Ekonomska Istraživanja, vol. 36, 2022, Art. no. 2123022, X. Jiang, J. Guo, A. Akbar, and P. Poulova.
[68] "Applicant qualifications and characteristics in STEM faculty hiring: An analysis of faculty and administrator perspectives," Int. J. STEM Educ., vol. 10, no. 1, pp. 1–20, 2023, J. Wu, T. Cropps, C. M. L. Phillips, S. Boyle, and Y. E. Pearson.
Int. J. Professional Bus. Rev., vol. 8, no. 6, 2023, Art. no. e02089. Albassam, W. A., "The power of artificial intelligence in recruitment: An analytical review of current AI-based recruitment strategies."
[70] A. S. George, "Analogous economic consequences of artificial intelligence," Partners Universal Int. Res. J., vol. 2, no. 3, pp. 20–39, 2023.
[71] In Digital Transformation, Strategic Resilience, Cyber Security, and Risk Management, F. Khan and A. Mer discuss the legal ramifications of using AI technology, specifically focusing on EU data protection policies. Emerald Publishing Limited, Bingley, U.K., 2023, pp. 119–141.
[72] Martins, V. W. B., L. V. Avila, L. D. S. L. Bastos, R. M. Fernandes, and P. A. Moreira, "Artificial intelligence and Industry 4.0? Validation of difficulties using Cronbach's alpha and the Lawshe technique in the context of a developing economy nation, Eng., Adv. Eng., vol. 4, no. 3, pp. 2336–2351, 2023.
[73] "The future of work: Implications of artificial intelligence on HR practices," by D. S. V. B. Vishwanath, Tuijin Jishu/J. Propulsion Technol., vol. 44, no. 3, pp. 1711–1724, 2023.