

EXPLORING THE ETHICAL IMPLICATIONS OF AI-ENHANCED HIRING PRACTICES IN DELHI NCR CONSULTING FIRMS

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ABSTRACT

The integration of artificial intelligence (AI) in the hiring process has revolutionized the way organizations seek and evaluate potential candidates, offering numerous advantages such as increased objectivity and efficiency. It is essential to recognize and address the substantial ethical implications associated with AI-enhanced hiring practices. In this study a qualitative analysis, conducted in the Delhi NCR region, involved 550 individuals with prior experience in AI-enabled recruiting, employing a deliberate sampling approach facilitated through social media channels. The research encompassed both inferential statistical techniques, such as t-tests and regression analysis, to uncover correlations and trends, and descriptive statistics to assess questionnaire data and provide a comprehensive overview. The study began by formulating five dependent variables and twenty-one independent variables, structured in the form of a Google Sheet, and the samples were collected in random sampling approaches. The collected data was subsequently subjected to statistical analysis using SPSS. This research offers valuable insights into the ethical considerations surrounding AI-driven hiring, shedding light on issues related to fairness, bias, privacy, and transparency, which are of paramount importance in the contemporary employment landscape.

Keywords: Artificial Intelligence, Ethical Implications, Dependent Variables, Independent Variables, T-Tests, Regression Analysis.

INTRODUCTION

The way humans live, work, and interact has been revolutionized by artificial intelligence (AI), which has swept across several sectors (Vishwanath 2020). Its influence goes much beyond science fiction, as seen by its practical uses in industries including finance, healthcare, entertainment, and manufacturing. One of these domains where AI has had the most significant and positive effects is human resources (HR) (Singh & Shaurya 2021). Organizations are realizing more and more how important human capital management is in the fast-paced, fiercely competitive global environment of today (Al-Kassem 2021). The cornerstone of a company's success, human resources not only guarantees that the right people are working in the right positions but also creates an environment where workers can grow, thrive, and help the firm achieve its strategic objectives. Because of these responsibilities, HR specialists are always searching for ways to enhance their processes and make them more effective, fair, and in line with corporate objectives (Atmaja *et al.* 2022). The reader is taken on a tour through the nexus of AI and HR, two powerful forces that are changing the nature of the contemporary workplace.

Our objective is to look at the different ways that AI is affecting HR practices, especially the ways that innovations powered by AI have the potential to completely change the HR role (Lee et al. 2019). AI has the power to transform human resource management practices, from hiring practices to talent management, employee engagement, and general HR operations. People are a company's most valuable asset (Rana & Sharma 2019).

The opportunities and risks associated with AI in HR as we traverse its complex landscape in the pages that follow (Alam 2020). AI can reduce recruiting prejudice, utilize predictive data for talent development, and improve employee engagement through individualized strategies (Chen 2023). But we will also address the big ethical questions, such as algorithmic fairness and data privacy. To offer a thorough grasp of the changing HR paradigm as we explore the nexus between artificial intelligence and human intelligence (Mikalef & Gupta 2021).

Artificial intelligence (AI) has garnered significant attention in recent times due to its swiftly increasing importance (Dwivedi et al. 2021). AI is now a major topic in talks nowadays, bolstered by developments in the internet and technology's impact on socio-economic and ethical aspects (Feijoo et al. 2020). Regulators are finding it difficult to comprehend the consequences of artificial intelligence for their citizens as businesses increase their investments in this field. Novel AI applications and services have been made possible by the confluence of "Big Data" with the rapidly expanding Internet of Things (IoT) (Jagatheesaperumal et al. 2020).

Generative AI has become a potent instrument in the constantly changing field of human resources (HR), necessitating defined goals from HR management (2023 Nah et al. [13]). While upholding moral norms and resolving the particular issues AI offers, these principles direct the strategic integration of AI (Tambe et al. 2019). HR executives prioritize fairness, openness, and bias reduction in all HR processes, with a focus on integrating ethical AI (Ochmann et al. 2019). The next step is to implement strong data governance, with an emphasis on data security, quality, and compliance with privacy laws to ensure that Generative AI findings are dependable (Gupta et al. 2023). Responsible AI use that improves rather than replaces human decision-making while maintaining a good applicant experience is essential for talent acquisition, a fundamental HR function. Likewise, HR directors want to give priority to Generative AI in order to customize staff development, designing learning programs that encourage both personal development and organizational adaptability (Yorks et al. 2022). As AI-driven programs to enhance work-life balance and track stress levels can result in a healthier, more engaged workforce, employee well-being follows suit. HR directors should give AI's ability to lessen prejudice in HR procedures a priority in their quest of diversity and inclusion as it will create a more equal workplace. AI is increasingly needed in HR planning and decision-making, particularly in the crucial area of leadership development, where it can identify high-potential individuals and create individualized strategies for their growth. As artificial intelligence (AI) alters HR practices, change management becomes increasingly important (Paschen et al. 2020). To ensure a seamless transition, effective communication, employee buy-in, and training are required. HR directors should also give AI-assisted decisionmaking a priority. By using AI's predictive analytics, they can use data to make well-informed decisions for strategic HR planning. Lastly, retraining HR personnel to properly manage Generative AI is a top need (Korzynski et al. 2023). This involves giving workers advanced knowledge of AI technology, data analysis techniques, and digital literacy. Together, these criteria give HR directors the ability to oversee the revolutionary possibilities of Generative AI, while guaranteeing that it complies with moral standards and improves the HR environment for the good of both workers and employers (Guerci et al. 2015).

A difficult ethical environment is presented by AI-enhanced recruiting methods in consulting businesses in Delhi NCR. They may lessen biases in the applicant selection process by providing the prospect of more effective, impartial, and data-driven recruiting procedures. But if these technologies are not carefully developed and applied, there is a serious risk that they may reinforce preexisting prejudices and perhaps make them worse. Ethical challenges include the fairness and transparency of algorithmic decision-making, the risk of discrimination against underrepresented groups, data privacy issues, and the potential erosion of the interpersonal aspect of hiring in an industry where relationships and soft skills matter. Striking the right balance between harnessing AI's benefits and ensuring ethical, equitable, and human-centric hiring practices is paramount to navigate this transformative landscape in Delhi NCR consulting firms.

The following is how the paper is set up: Using recent studies, Section 2 outlines the literature review. A comprehensive discussion of the proposed approach is given in Section 3. Section 4 looked at the findings acquired in the proposed system and compared the results to existing techniques, and Section 5 concludes the paper.

OBJECTIVES IN THIS STUDY

- To investigate the ethical concerns and implications associated with the use of AI in recruitment processes within consulting firms in Delhi NCR.
- To assess whether AI-based tools lead to bias and discrimination in hiring decisions.
- To propose ethical guidelines and best practices for AI-enhanced recruitment.

LITERATURE REVIEW

In recent years, there has been a growing body of research examining the intersection of artificial intelligence (AI) and the hiring process in the workplace. (Lin *et al.* 2020) discussed the possibilities of "equitech," AI systems designed to enhance equity in hiring. Implicit bias, a form of prejudice deeply ingrained in human decision-making, has been a significant concern in the hiring process. (Rodgers *et al.* 2020) laid the foundation for the Throughput Model, which elucidates how human decision-making is influenced by opinions, perceptions, and information utilization in the context of algorithmic Human Resource Management (HRM). This model provides insights into the potential for AI to support various methods of moral decision-making in HR. The development and application of AI systems in hiring, as explored by (Mariani & Lozada 2023) are not without challenges, as laws and regulations have been introduced to control their usage. While these AI technologies offer advantages, they also pose disadvantages that need attention. Ethical considerations are central in this evolving landscape, particularly in light of potential bias and discrimination issues.

In the realm of AI's economic impact, (oshi 2019) emphasized the potential for AI to boost the global economy significantly, with implications for scientific research, data analytics, and the proliferation of intelligent devices. The ethical dimensions of AI, particularly the responsibilities of developers and companies, were identified by (Martin 2019). Algorithms were seen as not neutral but imbued with values, influencing moral standards, rights, and dignity of stakeholders. (Raghavan 2019) delved into the specifics of algorithmic pre-employment evaluations, highlighting the need to uncover and reduce bias in these systems. (Yarger 2020) addressed the underrepresentation of minority IT workers and the role of algorithmic prejudice in exacerbating this issue. The legal framework for equitable hiring procedures was outlined by

(Gilbert 2006), with an emphasis on the ethical dimensions that extend beyond legal requirements. (Hunkenschroer & Kriebitz 2023) contributed to the conversation by examining the implications of human rights for AI-driven recruiting solutions. They assessed whether AI employment methods align with key human rights principles, including validity, autonomy, nondiscrimination, privacy, and transparency. (Christian 2021) explored the use of social media in the hiring process, uncovering ethical and legal concerns related to privacy and personal space violations when employers and recruiters delve into candidates' online profiles. Overall, these studies collectively underscore the profound impact of AI on hiring, ethical considerations, and the ongoing quest for fairness and equity in the workplace.

Problem Statement

Talent acquisition and recruiting are entering a new age marked by the quick integration of artificial intelligence (AI) into HR and hiring procedures (Allal-Cherif *et al.* 2021). In addition to raising a number of ethical issues that require our urgent attention, these AI-enhanced employment processes also raise questions about objectivity, efficiency, and perhaps better decision-making (Williamson *et.al* 2020). The fundamental issue with this dilemma is that AI-driven employment practices may be biased, discriminatory, or opaque, which might have serious repercussions for both people and society at large (Scatiggio 2022).

AI-enhanced hiring practices run the risk of perpetuating and even exacerbating existing biases in the recruitment process. Machine learning algorithms, when trained on historical hiring data, can inadvertently inherit and perpetuate the biases present in those data (Moore 2019), (George & Wooden 2023). This means that if past hiring decisions were influenced by race, gender, age, or other protected characteristics, AI systems may continue to favor certain demographic groups, thus perpetuating systemic inequalities (Zajko 2021). This inherent bias in AI hiring systems can result in unfair and discriminatory hiring outcomes, leading to a lack of diversity in the workplace and the marginalization of underrepresented groups (Nugent & Scott-Parker 2022). The lack of transparency and accountability in AI-enhanced hiring practices is a critical ethical concern. Many organizations use proprietary algorithms and models that are considered trade secrets, making it difficult for job applicants and even hiring managers to understand how decisions are made (Leicht-Deobald *et al.* 2019). This lack of transparency raises questions about fairness and the ability to challenge or contest hiring decisions (Kochling & Claus Wehner 2020). The black-box nature of AI systems makes it challenging to identify and rectify any biases or errors that may arise, further undermining trust in the hiring process.

RESEARCH DESIGN

1. The research design includes a qualitative analysis, which suggests that the study aims to understand the experiences and perspectives of individuals with prior experience in AI-enabled recruiting.
2. The research was conducted in the Delhi National Capital Region (NCR), specifying the geographic location where data collection took place.
3. The study involved 550 individuals as participants, indicating the sample size.
4. The research employed a deliberate sampling approach, implying that the researchers purposefully selected participants based on certain criteria or characteristics.
5. The study formulated five dependent variables and twenty-one independent variables, which indicates the key factors being analyzed and measured.
6. The data collection method involved the use of a Google Sheet to structure the variables, and random sampling approaches were used to gather the samples, revealing the data collection procedure.

7. The research encompassed inferential statistical techniques, such as t-tests and regression analysis, and the collected data was subjected to statistical analysis using SPSS, indicating the software used for data analysis.

Hypothesis

(i) Hypotheses for Ethical Awareness and Training (Mediating Variable):

- Null Hypothesis (H0): The level of ethical awareness and training does not mediate the relationship between the use of AI tools (IV) and Hiring Decision Bias (DV).
- Alternative Hypothesis (H1): The level of ethical awareness and training mediates the relationship between the use of AI tools (IV) and Hiring Decision Bias (DV).

(ii) Hypotheses for Demographic Diversity (Moderating Variable):

- Null Hypothesis (H0): Demographic diversity does not moderate the relationship between the use of AI tools (IV) and Hiring Decision Bias (DV).
- Alternative Hypothesis (H1): Demographic diversity moderates the relationship between the use of AI tools (IV) and Hiring Decision Bias (DV).

DATA COLLECTION

In the data collection process, we carefully selected 550 participants with firsthand experience in AI-enabled hiring processes. This group comprised 285 male and 265 female participants, all of whom were based in the Delhi National Capital Region (NCR). Their expertise in AI-driven hiring practices provided valuable insights into the study.

In demographic locations, our study has primarily centered on the urban environment of Delhi. This choice stems from the fact that urban areas, such as Delhi, have historically served as the epicenter for technological development, as highlighted by *Ahamed Younis in 2020 [40]*. Focusing on urban settings is essential because cities often serve as incubators for technological innovation, making them particularly relevant for research on AI-enabled hiring processes. While acknowledging the importance of rural and suburban contexts, this study aims to capture the pulse of cutting-edge technology adoption in the urban landscape of Delhi, where advancements in AI and hiring practices are rapidly evolving.

Frequency Table of Social Demographic Information

The accompanying table 1 and fig 1 presents frequencies, percentages, valid percentages, and cumulative percentages to provide a thorough overview of survey results across many demographic groups. The information is divided into five main demographic categories: Gender, Age, Education, Position, and Experience. There is also a further area that deals with the use of AI tools. 51.8% of respondents identified as male and 48.2% as female, indicating a fairly equal distribution of respondents by gender. An analysis-ready sample is guaranteed by this fair representation of genders.

The data indicates that a significant proportion of the respondents, at 28.2% of the total, are in the 25–34 age range, with the 35–44 age group coming in second at 27.1%. The poll sample spans a wide age range, with the younger demographic those under 25 making up 16.2% of the sample being split between respondents 45–54 and those 55 and over. Regarding

education, the vast majority of responders 34.7% have master's degrees, with bachelor's degrees following at 30.5%. Notably, 21.5% of the group hold a Ph.D., while just 13.3% claim merely having completed high school. This suggests that the group is well-educated and diversified.

Table 1 SOCIO DEMOGRAPHIC TABLE					
		Frequency	Percentage	Valid percentage	Cumulative percent
Gender	Male	285	51.8	51.8	51.8
	Female	265	48.2	48.2	100
Age	Under 25	89	16.2	16.2	16.2
	25-34	155	28.2	28.2	44.4
	35-44	149	27.1	27.1	71.5
	45-54	75	13.6	13.6	85.1
	55 and above	82	14.9	14.9	100
Education	High school	73	13.3	13.3	13.3
	Bachelor deg	168	30.5	30.5	43.8
	Master deg	191	34.7	34.7	78.5
	Phd	118	21.5	21.5	100
Position	Hr Personnel	130	23.6	23.6	23.6
	Hir Manager	112	20.4	20.4	44.0
	AI developer	118	34.2	34.2	78.2
	Others	120	21.8	21.8	100
Experience	0-2	86	15.6	15.6	15.6
	2-5	185	33.6	33.6	49.3
	5-10	198	36.0	36.0	85.3
	Above 10	81	14.7	14.7	100
AI tool use	No	184	33.5	33.5	33.5
	Yes	366	66.5	66.5	100

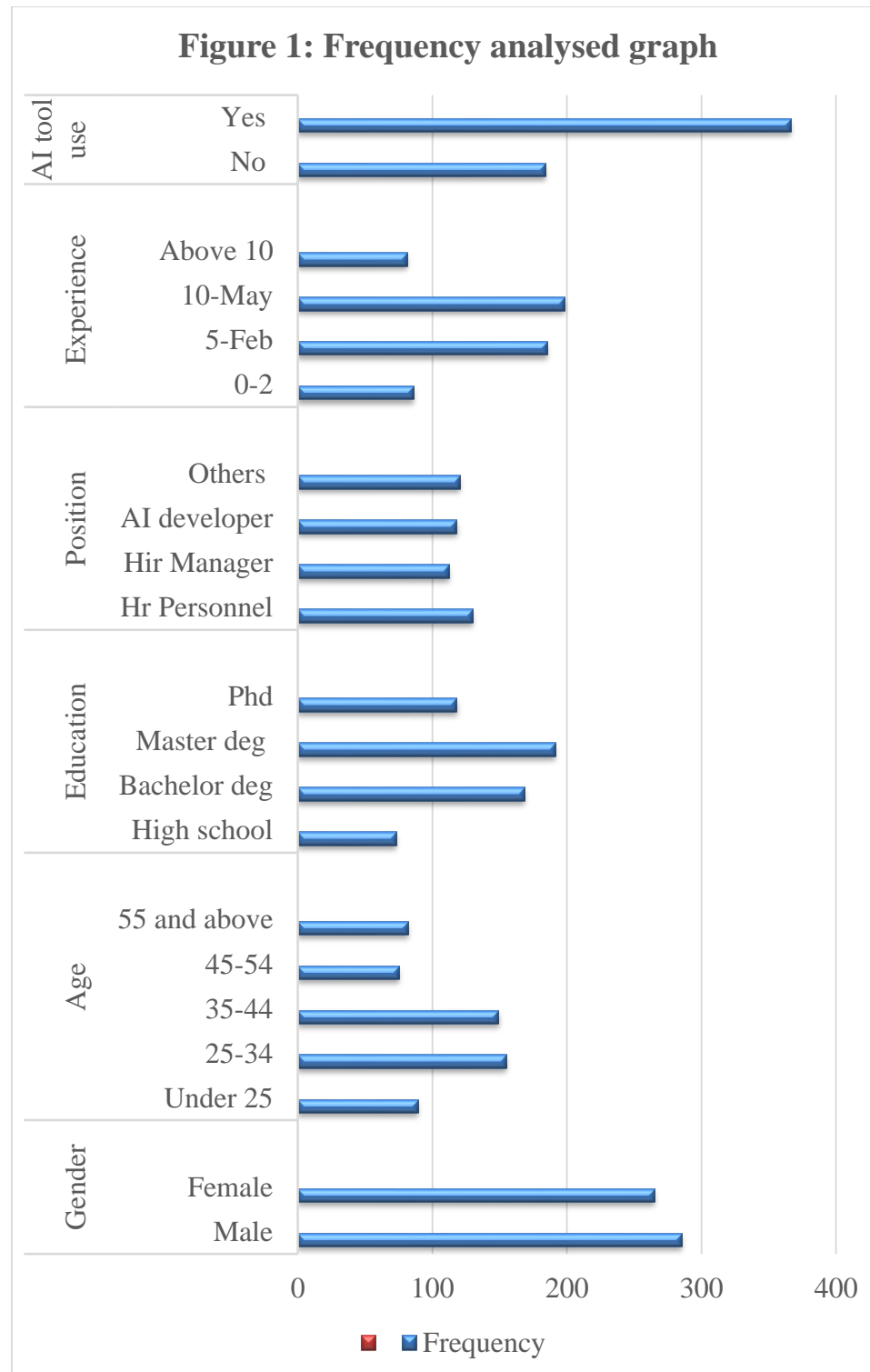


FIGURE 1
FREQUENCY ANALYSED GRAPH

Regarding the jobs of the respondents, the data shows that the largest group is represented by AI engineers (34.2%), HR personnel (23.6%), and hire managers (20.4%). Of

those who responded to the poll, 21.8% more identified as "Others," indicating a wide range of professional responsibilities. Regarding job experience, 36.0% of participants reported having 5–10 years of experience, whilst 33.6% reported having 2–5 years. In order to reflect a well-balanced representation of experience levels, the remaining percentages are split between those with less than two years of experience (15.6%) and those with more than ten years (14.7%).

Results from the poll show that 66.5% of participants utilize AI technologies, compared to 33.5% who do not. This offers insightful information about the use and prevalence of AI technology in the community under study. Cumulative percentages are included to guarantee that the overall sample size is properly taken into consideration in every category.

RESULT AND DISCUSSION

Correlation among Different Socio Demographic Factors

Table 2 shows that important insights into the correlations between a number of factors, such as gender, age, education, position, experience, and AI Tools Usage, are supplied by the correlation matrix that is provided. The Pearson correlation coefficient, which expresses the strength and direction of these correlations, is included in each matrix cell. Significantly, each variable's association with itself is represented by a diagonal cell, which is always 1. A modest but statistically significant negative connection has been found between age and education, which suggests that there is a slight tendency for people's levels of education to decline with age. A positive and statistically significant association has been found between age and position, suggesting that older persons are more likely to occupy top positions in the company. The minor negative connection between position and education suggests that jobs with somewhat lower rankings may be connected with greater levels of education. A positive and statistically significant link has been shown between experience and position, suggesting that those with greater experience typically occupy higher-ranking roles. The relationship between experience and AI Tools usage is negative, indicating that people with greater experience often utilize AI tools less frequently. Understanding how age, education, experience, and position relate to the use of AI technologies within the study's environment can be facilitated by these correlations, which offer insightful information about the dynamics between these factors.

Table 2 CORRELATION AMONG DIFFERENT SOCIO DEMOGRAPHIC FACTORS						
	Gender	Age	Education	Position	Experience	AI Tools Usage
Gender	1					
Age	-0.00487	1				
Education	-0.0362	.612**	1			
Position	0.03185	.239**	-0.04361	1		
Experience	-0.0079	-0.00334	-0.00686	0.011941	1	
AIToolsUsage	0.00504	-0.02849	0.005729	-0.019	-0.03053	1

** . Correlation is significant at the 0.01 level (2-tailed).

Respondents Agreement Regarding Ethical Reduces of AI based Hiring and their Relationship among Variables

Table 3 FREQUENCY TABLE 2			
Training	Questions	Mean score	Variance
Ethical Awareness and Training (EAT)			
EAT 1	To what extent have you received ethical training related to AI-based recruitment practices.	3.54 ± 1.003	1.007
EAT 2	How confident are you in recognizing and addressing ethical concerns in AI-enhanced hiring.	3.68 ± 0.950	0.903
EAT 3	Have you noticed ethical concerns related to AI-enhanced hiring practices in your firm? If so, please describe	3.59 ± 0.956	0.931
Demographic Diversity (Moderating Variable)			
DD 1	How would you describe the demographic diversity within your firm's applicant pool.	3.64 ± 0.949	0.900
DD 2	How diverse is your current workforce in terms of demographics (e.g., age, gender, ethnicity).	3.65 ± 0.900	0.810
AI Use and Ethical Concerns			
AIEC 1	To what extent do you believe AI tools may introduce bias in the hiring process	3.11 ± 1.303	1.697
AIEC 2	How familiar are you with the ethical principles and guidelines surrounding AI use in recruitment	3.58 ± 0.950	0.903
Ethical Awareness and AI Tools			
EAAI 1	Do you think that ethical awareness and training play a role in mitigating potential biases introduced by AI tools in hiring	3.56± 0.919	0.844
EAAI 2	How confident are you in your ability to address ethical concerns related to AI-enhanced hiring in your role.	3.55± 0.864	0.747
EAAI 3	To what extent does your firm provide ongoing ethical training and guidance specifically related to the use of AI tools in hiring.	3.53± 0.942	0.887
EAAI 4	How frequently do you engage in discussions or training sessions related to ethical considerations in AI-enhanced hiring.	3.63± 0.961	0.923
Demographic Diversity and AI Tools			
DDAIT 1	In your opinion, does the demographic diversity of the applicant pool impact the potential for bias when using AI tools in hiring.	3.60± 0.955	0.911
DDAIT 2	How does demographic diversity within the workforce affect the effectiveness of AI tools in hiring decisions	3.50± 0.921	0.848
AI Use and Hiring Decision Bias			
AIHDB 1	Have you noticed instances of bias in hiring decisions attributed to the use of AI tools in your firm	3.49 ± 0.946	0.895
AIHDB 2	How concerned are you about the potential for AI-based hiring tools to produce biased outcomes	3.59± 0.938	0.880
AIHDB 3	To what extent do you believe that AI tools can be designed to minimize hiring decision bias	3.56± 0.915	0.837
Ethical Guidelines and Best Practices			
EGBP1	Do you believe that there is a need for specific ethical guidelines and best practices for using AI tools in recruitment	3.52 ± 0.963	0.928
EGBP 2	If you believe ethical guidelines are needed, what areas should they cover? (Select all that apply)	3.53 ± 0.930	0.865
EGBP 3	How confident are you in your firm's ability to establish and implement ethical guidelines for AI-enhanced recruitment	3.58 ± 0.921	0.849

Several questions about AI Use and Ethical Concerns (AIEC), Demographic Diversity and AI Tools (DDAIT), AI Use and Hiring Decision Bias (AIHDB), Ethical Guidelines and Best Practices (EGBP), and Ethical Awareness and Training (EAT) are included in the provided questionnaire are shown in table 3. Each question on the questionnaire aims to gather information on respondents' opinions, experiences, and views about AI-based recruiting procedures and moral hiring practices. The overall patterns in replies as well as the degree of agreement or consensus among participants are shown by the mean scores and variations for each question.

In the Survey Results, Several Notable Trends and Insights Can be Identified

The respondents exhibited a moderate level of confidence in addressing ethical issues in AI-enhanced hiring, as evidenced by the relatively high mean scores of the Ethical Awareness and Training (EAT) items. These items include ethical training related to AI-based recruitment practices (EAT 1), confidence in recognizing and addressing ethical concerns (EAT 2), and the presence of ethical concerns in the firm (EAT 3). The variance values imply that there is some degree of participant consistency in the replies provided in these areas. The Demographic Diversity (DD) questions show that respondents believe there is a modest amount of diversity in the application pool (DD 1) and the present workforce (DD 2). These items look at the diversity in these areas. A somewhat consistent impression among participants is shown by the variance values.

The mean scores for the AI Use and Ethical Concerns (AIEC) questions, which include being familiar with ethical principles (AIEC 2) and the possibility of bias being introduced by AI tools (AIEC 1), are moderate. There is more variation in respondents' judgments of bias introduced by AI tools, as seen by AIEC 1's rather large variance. The responses to the Ethical Awareness and AI Tools (EAAI) questions show that ethical awareness and training are commonly seen as important factors in reducing the biases brought by AI tools (EAAI 1). Also, they exhibit a moderate level of confidence while handling ethical issues (EAAI 2). The variance values indicate that participants have a considerable degree of agreement in these areas. The items in the Demographic Diversity and AI Tools (DDAIT) series examine the relationship between hiring efficacy and demographic diversity and bias potential. Respondents generally agree (moderately) that there is a link between demographic diversity and the possibility of prejudice (DDAIT 1). The efficacy of AI tools in recruiting choices (DDAIT 2), on the other hand, has a somewhat lower mean score, suggesting a modest degree of perceived efficacy. Response variability is shown by the variance values.

The AI Use and Hiring Decision Bias (AIHDB) items indicate that respondents have observed biased hiring decisions that they attribute to AI tools (AIHDB 1) and they are concerned about biased results (AIHDB 2). With a mean score of 3 (moderate), the notion that AI technologies can be made to decrease bias is rated. Variance values show that answers in these domains are generally consistent. The Ethical standards and Best Practices (EGBP) elements point to the idea that employing AI tools for hiring calls for the establishment of ethical standards and best practices (EGBP 1). The degree of respondents' confidence in their company's capacity to create and execute ethical policies is moderate (EGBP 3). A degree of consistency in these answers is shown by the variance values.

T Test

Comparing the mean scores of two sets of individuals or conditions is done using t-tests. T-tests come in two varieties: separate samples. Compare the means of two distinct groups of individuals or conditions using the t-test. Using a t-test, compare the average scores of the same participants again.

From the data shown in table 4 you've given that one-sample t-tests for a variety of variables were conducted. To determine the significance of variations between sample means and a test value typically set at 0 as a reference point a crucial statistical analysis tool is the t-test. Considering sample size and standard deviation, the t-value is a crucial measure. Higher t-values indicate larger differences between the sample mean and the test result. Degrees of freedom (df) play a crucial role, especially in t-tests, since they represent the number of variables that may change during the calculation of a statistic, which is frequently correlated with sample size. A crucial indication, the two-tailed significance (Sig.) value shows the likelihood that the null hypothesis is correct and that the observed results or even more extreme outcomes would materialize. The p-values in your instances are quite near to 0, indicating that the results are statistically significant. Furthermore, the range within which the genuine population mean difference is expected to lie with 95% confidence, as well as the variance between the test result and the sample mean, are all provided by the mean difference and the 95% confidence interval of the difference. For researchers and analysts to assess the importance and dependability of their findings in a variety of subject areas, these statistical components are essential tools.

Table 4						
T TEST ONE-SAMPLE TEST						
	Test Value = 0					
	<i>t</i>	<i>df</i>	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
EAT	115.371	549	0.000	3.60242	3.5411	3.6638
DD	111.170	549	0.000	3.64818	3.5837	3.7126
AIEC	88.003	549	0.000	3.34545	3.2708	3.4201
EAAI	130.436	549	0.000	3.56591	3.5122	3.6196
DDAIT	108.400	549	0.000	3.54909	3.4848	3.6134
AIHDB	117.004	549	0.000	3.54545	3.4859	3.6050
EGBP	122.768	549	0.000	3.54242	3.4857	3.5991

The p-value is very close to 0 ($p < 0.0001$), which means that for each variable tested (Ethical Awareness and Training, Demographic Diversity, AI Use and Ethical Concerns, Ethical Awareness and AI Tools, Demographic Diversity and AI Tools, AI Use and Hiring Decision Bias, Ethical Guidelines and Best Practices), the t-value differs significantly from the test value (0). According to this, there may be a large difference between the means of these variables and zero. In every instance, the mean differences are positive, suggesting that the sample means exceed the test value (0). This indicates that each sample mean is higher than zero. All of the differences' 95% confidence intervals are positive and exclude 0.

Relationship among AI use in having, Ethical Guidelines in using AI and their Mediating and Moderating Variables

Correlation coefficients can be used to statistically summarize the linear relationship between the direction and strength of two variables. These are the two main correlation coefficients that are found: - The Pearson product-moment correlation between one continuous and one dichotomous variable, or between two continuous variables.

Table 5 CORRELATIONS TABLE 1							
	EAT	DD	AIEC	EAAI	DDAIT	AIHDB	EGBP
EAT	1						
DD	0.427**	1					
AIEC	0.302**	0.401**	1				
EAAI	0.528**	0.439**	0.356**	1			
DDAIT	0.398**	0.483**	0.348**	0.523**	1		
AIHDB	0.540**	0.429**	0.388**	0.499**	0.418**	1	
EGBP	0.473**	0.401**	0.332**	0.497**	0.437**	0.484**	1

**. Correlation is significant at the 0.01 level (2-tailed).

An invaluable resource for comprehending the connections between various variables or constructs is the correlation matrix that is supplied. To determine the direction and intensity of these correlations, Pearson correlation coefficients are used. The significance threshold for the correlation is 0.01 (2-tailed). This suggests that the variables with the labels EAT, DD, AIEC, EAAI, DDAIT, AIHDB, and EGBP have strong and positive associations. This implies that the others tend to rise together with the increase in one of these variables. The moderate to high strength of these associations suggests that these variables are related to one another and probably have similar underlying elements in your dataset.

Influence of Ethical Awareness and Training on Hiring Decision via AI Tools

A collection of variables' correlations and ANOVA results are shown in the tables 5-7 which may be used to evaluate the relationship between the variables and test hypotheses. The variables' Pearson correlation coefficients are displayed in the correlation matrix. The moderately positive correlation of 0.540 between EAT and AIHDB, for instance, indicates that a rise in one variable is likely to result in an increase in the other. The link between these factors is further investigated in the ANOVA table. If there is no significant link between the variables, this is the null hypothesis that is often tested in an ANOVA. The results show that at least one of the variables (EAT, AIHDB, EGBP, or DDAIT) has a statistically significant impact on the outcome. The regression model appears to be significant in this situation ($F = 104.913$, $p < 0.001$). As a result, the data points to a substantial link between these factors, rejecting the null hypothesis hence the alternates hypothesis is accepted and The level of ethical awareness and training mediates the relationship between the use of AI tools (IV) and Hiring Decision Bias (DV). This indicates that a significant predictor of the dependent variable is at least one of the independent variables.

Table 6 CORRECTION TABLE					
		EAT	AIHDB	EGBP	DDAIT
Pearson Correlation	EAT	1	0.54	0.473	0.398
	AIHDB	0.54	1	0.484	0.418
	EGBP	0.473	0.484	1	0.437
	DDAIT	0.398	0.418	0.437	1

Table 7 REGRESSION ANALYSIS - ANNOVA TABLE 1					
Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	107.649	3	35.883	104.913	.000 ^b
Residual	186.747	546	0.342		
Total	294.397	549			

Influence of Demographic Diversity Hiring Decision via AI Tools

Tables 8 & 9 presents the findings of a regression analysis that may be utilized to evaluate the hypothesis concerning the moderating impact of demographic diversity on the association between hiring decision bias (DV) and the use of AI technologies (IV), the independent variable. Under this situation, the null hypothesis (H0) asserts that hiring decision bias and the use of AI tools are not influenced by demographic diversity. In fact, demographic variety appears to mitigate this association, according to the alternative hypothesis (H1). The table's "Regression" row indicates that the F-statistic is 82.659 and the p-value (Sig.) is less than 0.05, at.000b. This implies that the independent variables collectively have a significant impact on the dependent variable. These results, we can conclude that there is evidence to support the alternative hypothesis (H1), indicating that demographic diversity moderates the relationship between the use of AI tools and Hiring Decision Bias, as the IVs collectively influence the DV.

Table 8 CORRELATIONS					
		DD	DDAIT	AIHDB	EGBP
Pearson Correlation	DD	1.000	0.483	0.429	0.401
	DDAIT	0.483	1.000	0.418	0.437
	AIHDB	0.429	0.418	1.000	0.484
	EGBP	0.401	0.437	0.484	1.000

Table 9					
REGRESSION ANALYSIS - ANOVA					
Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	101.559	3	33.853	82.659	.000 ^b
Residual	223.614	546	0.41		
Total	325.173	549			

CONCLUSION

The study concludes by highlighting the significant influence of artificial intelligence on employment practices in the Delhi NCR region and emphasizing the important ethical concerns that emerge in this digital age. While there are clear advantages to objectivity and efficiency when it comes to AI-driven hiring, there are also serious issues about privacy, fairness, transparency, and potential bias. The results underscore the significance of confronting and resolving these moral conundrums in order to guarantee equitable and moral recruitment practices. The statistical studies carried out in this paper offer compelling proof of a meaningful association between the dependent variable and one or more independent variables, highlighting the impact of AI-driven hiring on how employment practices will develop in the future. Encouraging inclusive and equal possibilities in the dynamic labor market and preserving the integrity of hiring practices need companies and politicians to negotiate these ethical issues in parallel with the progress of AI technology. (i) The data points to a substantial link between these factors, rejecting the null hypothesis hence the alternates hypothesis is accepted and The level of ethical awareness and training mediates the relationship between the use of AI tools (IV) and Hiring Decision Bias (DV). This indicates that a significant predictor of the dependent variable is at least one of the independent variables. (ii) These results, we can conclude that there is evidence to support the alternative hypothesis (H1), indicating that demographic diversity moderates the relationship between the use of AI tools and Hiring Decision Bias, as the IVs collectively influence the DV.

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