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EXPLORING THE ROLE OF IMPLICIT BIAS IN HIRING DECISIONS: AN EMPIRICAL STUDY OF PRIVATE BANKS IN SAGAR DISTRICT

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Running Title: Implicit Bias in Hiring Decisions

ABSTRACT

Implicit bias in recruitment continues to challenge efforts toward equitable and inclusive hiring practices, impacting candidate evaluation and overall workplace diversity. This paper presents a systematic review of peer-reviewed literature and an empirical analysis of implicit bias in hiring, examining how unconscious biases shape candidate selection, hinder diversity, and reinforce structural inequalities. The study employs a mixed-methods approach, incorporating structured surveys and regression analysis to measure the impact of gender, race, age, and affinity bias on hiring decisions within private banks in Sagar District. Findings indicate that structured interviews and blind recruitment can partially reduce bias; however, the pervasive nature of implicit attitudes underscores the need for ongoing research and adaptive organizational practices. The study identifies key gaps in existing literature and proposes future research directions to enhance understanding and inform more effective interventions. By providing actionable insights and strategic recommendations, this paper aims to support HR professionals and organizations in cultivating fairer recruitment practices and fostering diverse and inclusive workplaces.

Keywords - Implicit bias, Recruitment bias, Unconscious bias, Diversity, Hiring practices

1.0 INTRODUCTION

Implicit bias in recruitment represents a critical challenge for organizations striving to create diverse workplaces. Unlike explicit biases, which are consciously held, implicit biases operate subtly, often outside conscious awareness, affecting decisions and evaluations in ways that can perpetuate inequalities in hiring. Research has shown that unconscious preferences based on factors such as gender, race, and age can significantly influence candidate assessments (Bertrand & Mullainathan, 2004; Greenwald & Banaji, 1995; Quillian et al., 2017; Rooth, 2010), often leading to unfair advantages or disadvantages for certain groups. This bias in recruitment not only undermines the principles of equity and fairness but also hinders organizational efforts to benefit from diverse perspectives (Eagly & Carli, 2007; Moss-Racusin et al., 2012; Pager & Shepherd, 2008), which are linked to enhanced innovation and improved problem-solving.

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Although significant research has been conducted on implicit bias in hiring, there remains a gap in understanding how these biases function in different cultural contexts, particularly in non-Western economies like India. Existing studies predominantly focus on Western labor markets, leaving an opportunity for research that examines how implicit bias manifests in emerging economies (Carlsson & Rooth, 2007; Derous & Ryan, 2019). Additionally, prior studies often overlook the intersectionality of biases—how multiple identity factors interact to shape hiring decisions (Crenshaw, 1989; Kang et al., 2016). Addressing this gap is crucial for developing more inclusive hiring policies that are globally relevant.

With the increased use of technology in hiring, such as automated screening tools and artificial intelligence-driven platforms, there is growing concern that these tools may inadvertently replicate and amplify existing biases if not properly designed and monitored (Binns, 2020; Obermeyer et al., 2019; Dastin, 2018). Addressing implicit bias is thus essential for organizations committed to ethical, unbiased hiring practices and for those seeking to foster workplace environments that truly reflect the diversity of the society in which they operate. This paper aims to explore the scope and impact of implicit bias in recruitment, offering insights into current research and practical recommendations for reducing bias at various stages of the hiring process.

Scope: This study explores the scope of implicit biases in recruitment by incorporating both Western and non-Western perspectives. While much of the existing literature focuses on Western economies, this research seeks to bridge the gap by examining implicit bias in private banks within India, particularly in the Sagar District. The study considers a broad range of psychological, organizational, and technological factors influencing implicit bias, drawing from fields such as human resource management, cognitive psychology, and artificial intelligence. This approach provides a comprehensive understanding of how bias operates across diverse hiring environments.

Significance: The significance of this research extends beyond theoretical contributions to practical applications in organizational hiring policies. By identifying key biases that influence hiring decisions, the study offers actionable recommendations for HR professionals, policymakers, and corporate leaders. As organizations worldwide recognize the value of diverse workforces in driving innovation and performance, it becomes essential to address the unconscious biases that hinder equitable hiring. This study also emphasizes the implications of emerging hiring technologies, particularly AI-driven recruitment tools, which may either mitigate or perpetuate bias depending on their design and implementation. Understanding these dynamics will help organizations implement effective bias-reduction strategies, fostering more inclusive workplaces that align with global diversity and inclusion standards. With the increased use of technology in hiring, such as automated screening tools and artificial intelligence-driven platforms, there is growing concern that these tools may inadvertently replicate and amplify existing biases if not properly designed and monitored (Binns, 2020; Obermeyer et al., 2019; Dastin, 2018). Addressing implicit bias is thus essential for organizations committed to ethical, unbiased hiring practices and for those seeking to foster workplace environments that truly reflect the diversity of the society in which they operate. This paper aims to explore the scope and impact of implicit bias in recruitment, offering insights into current research and practical recommendations for reducing bias at various stages of the hiring process.

2.0 METHODOLOGY

This study employs a mixed-methods research design, integrating both quantitative and qualitative approaches to provide a comprehensive analysis of implicit bias in hiring.

Research Design: The study follows a sequential explanatory design, where quantitative data collection and analysis are conducted first, followed by qualitative insights to elaborate on the findings.

2.1 Data Collection:

Primary Data: A structured survey was administered to employees in HR and recruitment positions within private banks in Sagar District. The survey was designed to capture perceptions of implicit bias and hiring preferences.

Secondary Data: The study incorporates an extensive review of existing literature, including peer-reviewed journal articles, reports on diversity hiring, and case studies on recruitment bias.

2.2 Sampling Strategy:

Target Population: HR professionals and hiring managers in private banks in Sagar District.

Sampling Technique: A purposive sampling method was employed to ensure participation from individuals directly involved in recruitment decision-making.

Sample Size: A total of 200 participants were surveyed, ensuring a diverse representation across age, gender, and experience levels.

2.3 Data Analysis:

Quantitative Analysis: Statistical methods, including regression analysis, were applied to examine the relationships between implicit bias factors and hiring decisions. Descriptive statistics were used to summarize demographic characteristics.

Qualitative Analysis: Open-ended responses were analysed using thematic analysis to identify recurring patterns and insights related to bias in hiring.

Software Used: Data analysis was conducted using SPSS for statistical computations and NVivo for qualitative data coding.

2.4 Ethical Considerations:

Participants were provided with informed consent forms, ensuring voluntary participation and anonymity and Data confidentiality was maintained throughout the research process, and bias mitigation techniques were employed to minimize researcher influence.

This methodological approach ensures a robust and comprehensive analysis of implicit bias in recruitment, contributing to both theoretical insights and practical recommendations for HR professionals.

With the increased use of technology in hiring, such as automated screening tools and artificial intelligence-driven platforms, there is growing concern that these tools may inadvertently replicate and amplify existing biases if not properly designed and monitored (Binns, 2020; Obermeyer et al., 2019; Dastin, 2018). Addressing implicit bias is thus essential for organizations committed to ethical, unbiased hiring practices and for those seeking to foster workplace environments that truly reflect the diversity of the society in which they operate. This paper aims to explore the scope and impact of implicit bias in recruitment, offering insights into current research and practical recommendations for reducing bias at various stages of the hiring process.

2.5 Limitations

- Sample Size Constraints: Findings are limited to the private banking sector in Sagar District and may not be generalizable to broader populations.
- Self-Reported Data: Responses may be subject to social desirability bias.

This methodological framework ensures a robust analysis of implicit bias in recruitment, contributing to a deeper understanding of discriminatory hiring patterns and diversity challenges in the workplace.

3.0 STATISTICAL ANALYSIS

This study employs a range of statistical techniques to analyze the impact of implicit biases on hiring decisions. The analysis is structured to identify patterns, relationships, and significance levels among different bias factors.

Descriptive Statistics Used to summarize demographic characteristics of survey respondents, including gender, age, experience level, and hiring responsibilities. Measures of central tendency (mean, median, mode) and dispersion (standard deviation, variance) were computed to understand trends in responses.

Correlation Analysis: Pearson's correlation coefficient was employed to assess the strength and direction of relationships between implicit bias factors (gender, ethnicity, age, affinity) and hiring decisions. Identified statistically significant correlations at the 95% confidence interval ($p < 0.05$).

Regression Analysis: A multiple linear regression model was developed to quantify the effect of implicit bias variables on hiring outcomes. The model controlled for confounding variables, such as industry experience and organizational hiring policies. Standardized beta coefficients were reported to compare the relative impact of each predictor.

ANOVA (Analysis of Variance): One-way ANOVA was conducted to test for significant differences in hiring decisions across different demographic groups. Post hoc tests (Tukey's HSD) were applied to pinpoint specific group differences.

Factor Analysis: Exploratory factor analysis (EFA) was performed to identify underlying constructs influencing hiring decisions. Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity were used to confirm data suitability.

Software Used: SPSS were used for statistical computations to ensure accurate and reproducible results. The application of these statistical techniques provides a rigorous framework for evaluating implicit bias in hiring, ensuring robust and generalizable findings. With the increased use of technology in hiring, such as automated screening tools and artificial intelligence-driven platforms, there is growing concern that these tools may inadvertently replicate and amplify existing biases if not properly designed and monitored (Binns, 2020; Obermeyer et al., 2019; Dastin, 2018). Addressing implicit bias is thus essential for organizations committed to ethical, unbiased hiring practices and for those seeking to foster workplace environments that truly reflect the diversity of the society in which they operate. This paper aims to explore the scope and impact of implicit bias in recruitment, offering insights into current research and practical recommendations for reducing bias at various stages of the hiring process.

3.1 Forms of Implicit Bias Impacting Hiring Decisions

Implicit bias in recruitment encompasses a wide range of unconscious preferences and stereotypes that influence hiring decisions. These biases operate without intentional awareness and are typically shaped by social, cultural, and psychological factors. Understanding the various forms of implicit bias is essential for addressing the inequities they perpetuate in the hiring process. This section explores key forms of implicit bias—gender bias, racial and ethnic bias, and age bias along with relevant psychological and organizational theories to frame each type.

Gender Bias - Gender bias remains one of the most well-documented forms of implicit bias in recruitment. Stereotypes related to gender roles can subtly influence hiring decisions, often favoring male candidates in fields historically dominated by men and female candidates in those traditionally associated with women (Moss-Racusin, Dovidio, Brescoll, Graham, & Handelsman, 2012). Research indicates that both male and female recruiters may harbor gender-based biases, resulting in a preference for male candidates in leadership or technical roles and for female candidates in nurturing or supportive roles. These biases often operate unconsciously, reinforcing traditional gender norms and limiting the diversity of candidates selected for various positions.

Social role theory (Eagly, 1987) offers a psychological framework for understanding gender bias, positing that societal expectations about the roles of men and women influence the perceptions of their suitability for certain jobs. These stereotypes can hinder women's advancement in male-dominated sectors and may influence hiring decisions even when recruiters explicitly strive for fairness.

Race and Ethnic Bias - Racial and ethnic bias is another prevalent form of implicit bias that significantly impacts hiring decisions. Studies consistently show that candidates with "ethnically ambiguous" or minority-sounding names are less likely to be shortlisted or receive job offers compared to their White counterparts with identical qualifications (Bertrand & Mullainathan, 2004). These biases are particularly troubling because they perpetuate structural inequalities in employment, limiting opportunities for racial and ethnic minorities and reinforcing cycles of socioeconomic disadvantage. The stereotype content model (Fiske, Cuddy, & Glick, 2002) can help explain how racial and ethnic biases form in the recruitment process. This model suggests that people hold stereotypes about others based on two dimensions: warmth and competence. Applicants from certain racial or ethnic groups may be perceived as lacking competence or not fitting the ideal candidate profile for particular roles, especially in competitive or high-status professions. Such perceptions lead to biased judgments and unequal access to opportunities.

Age bias - discrimination against candidates based on age—can manifest as both a preference for younger candidates and a bias against older candidates. Younger candidates are often seen as more adaptable, energetic, and technologically proficient, whereas older candidates may be perceived as less flexible or less capable of keeping up with new trends. Implicit age bias can influence decisions, particularly in industries such as technology or creative fields, where youth is often equated with innovation (Posthuma & Campion, 2009). **The age stereotype content model** (Kite & Johnson, 1988) suggests that older individuals are often viewed with ambivalence, perceived as highly competent but low in warmth. This stereotype can lead to exclusionary hiring practices that disadvantage older workers despite their experience and qualifications.

Affinity bias - Affinity bias, also known as similarity bias, refers to the unconscious tendency to favor individuals who share similar backgrounds, interests, or characteristics with oneself. It can lead to preferential treatment in hiring decisions, often at the expense of diversity and merit-based evaluation (Greenwald & Pettigrew, 2014). This bias typically emerges from a sense of comfort and trust with those perceived as similar, reinforcing homogeneity in teams. Addressing affinity bias is essential to fostering inclusive and equitable workplace practices.

3.2 Theoretical Perspectives on Implicit Bias

Several psychological and organizational theories help explain the underlying mechanisms of implicit bias in hiring. These theories provide a broader context for understanding how biases form and influence decision-making processes in recruitment.

Social Cognition Theory (Fiske & Taylor, 1991) posits that people categorize others based on mental shortcuts, or heuristics, which are influenced by past experiences, stereotypes, and social norms. These cognitive shortcuts allow for quicker judgments but often lead to biased decisions in complex situations like hiring.

Stereotype Activation and Application (Devine, 1989) explains how certain cues automatically trigger stereotypes, even when individuals consciously reject biased beliefs. In recruitment, this means that recruiters may unknowingly apply gendered or racial stereotypes to candidates without being aware of it.

Implicit Association Theory (Greenwald & Banaji, 1995) underpins much of the research on implicit bias. It suggests that people harbor unconscious associations that can influence their attitudes and behaviors, including their hiring decisions. These associations can shape candidates' perceptions in ways inconsistent with their qualifications.

3.3 Previous Studies:

In this study, the researcher found that candidates with an ethnic name and accent were judged more negatively, while those with just one ethnic marker, like a name without an accent, were viewed more positively. This highlights how multiple ethnic cues can trigger unconscious bias. The research also introduces "modern ethnicity bias", showing that even those who don't overtly discriminate can still make biased decisions subconsciously. The study effectively isolates how these factors influence interview outcomes using controlled experiments. Overall, the paper sheds light on the subtle ways biases can impact hiring, even when candidates are well-qualified. (Purkiss et al., 2006)

In this seminal study, Bertrand and Mullainathan examined the impact of racial bias in the U.S. labor market using a field experiment. The researchers sent out fictitious resumes with names perceived as either White or African-American to job openings. Despite identical qualifications, resumes with White-sounding names received 50% more callbacks than those with African-American-sounding names. This study underscores the existence of implicit racial bias in hiring, as recruiters appeared to unconsciously Favor White applicants. The findings highlighted systemic barriers to employment for minority groups and called for structural changes in recruitment processes to reduce such biases. (Bertrand, M., & Mullainathan, S. (2004)

This meta-analysis synthesized data from numerous field experiments conducted over several decades to assess trends in racial discrimination in hiring. The study revealed that racial bias in callbacks for job applications has remained alarmingly consistent, contradicting the notion of social progress in this domain. Employers were found to systematically prefer White applicants over Black and Hispanic applicants, even when qualifications were identical. The authors suggest that while overt forms of discrimination may have decreased, implicit biases remain a significant barrier to achieving workforce diversity. This work emphasizes the importance of sustained efforts to combat discrimination in recruitment. (Quillian, L., Pager, D., Hexel, O., & Midtbøen, A. H. (2017)

This study investigated the intersection of gender and racial stereotypes in evaluating postdoctoral candidates in STEM fields. Faculty members were presented with fictitious profiles of candidates with varying gender and racial markers. Results indicated that women and minority candidates were systematically rated lower in terms of competence and hiring ability compared to their White male counterparts. The findings shed light on how deeply ingrained stereotypes about race and gender persist in academic and professional evaluations, thus affecting the career advancement of underrepresented groups. The authors call for comprehensive diversity training and unbiased evaluation methods in STEM hiring processes. (Eaton, A. A., Saunders, J. F., Jacobson, R. K., & West, K. (2019)

Through a meta-analysis of over 492 studies, this paper examined interventions designed to reduce implicit biases. The findings revealed that while short-term interventions such as training programs and exposure to counter-stereotypical exemplars can temporarily alter implicit biases, their effects often fade over time. The study highlights the complexity of changing deep-seated implicit associations and suggests that systemic solutions, rather than individual interventions alone, are necessary to combat discrimination effectively. The authors propose integrating bias reduction strategies into organizational policies to create a more equitable hiring process. (Forscher, P. S., Lai, C. K., Axt, J. R., et al. (2019)

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This paper explores how algorithmic decision-making systems can either perpetuate or mitigate bias in hiring. Binns critically evaluates the fairness of automated hiring tools and identifies potential risks of algorithmic discrimination. The study points out that biased data inputs often lead to biased outcomes, with minority groups disproportionately affected. However, the author also highlights the potential of algorithms to improve hiring practices if designed with fairness criteria. This study serves as a call to action for developers and employers to ensure ethical AI practices in recruitment. (Binns, R. (2020)

This study investigated how evaluators process conflicting information about job candidates with varying racial backgrounds. The researchers found that evaluators placed greater weight on negative information for minority candidates compared to White candidates, a phenomenon known as differential weighting. This implicit bias occurs even among individuals who claim to hold egalitarian views, suggesting that unconscious stereotypes can significantly influence decision-making. The study emphasizes the need for structured evaluation frameworks to mitigate subjective biases in hiring. Hodson, G., Dovidio, J. F., & Gaertner, S. L. (2002)

Rooth's field experiment examined whether implicit associations, as measured by the Implicit Association Test (IAT), influenced callback rates for job applicants with ethnic-sounding names. The findings showed a significant correlation between implicit bias scores and discriminatory hiring decisions, highlighting the unconscious nature of bias in recruitment. This research underscores the importance of raising awareness about implicit bias and implementing blind recruitment practices. Rooth, D. O. (2010)

Another study conducted a correspondence experiment in Sweden to identify ethnic discrimination in hiring. The researchers sent fictitious resumes with Arabic and Swedish names to employers. Despite identical qualifications, applicants with Arabic-sounding names received fewer callbacks than those with Swedish names. This study highlights the pervasiveness of ethnic discrimination in labor markets and suggests the need for stronger anti-discrimination policies. (Carlsson, M., & Rooth, D. O. (2007)

This study reviewed the methodology and findings of field experiments designed to identify workplace discrimination. Pager and Western highlighted that field experiments are powerful tools for uncovering subtle biases that traditional surveys fail to capture. The study emphasizes the need for interventions to address systemic discrimination in recruitment practices. (Pager, D., & Western, B. (2012)

3.4 Thematic Analysis

Theme	Findings	Implications	Supporting Studies
Gender Bias in Hiring Decisions	Male candidates are often preferred for technical roles (M = 3.81, SD = 1.179), whereas female candidates are perceived to excel in interpersonal roles (M = 4.00, SD = 1.139).	Reinforces gender stereotypes, limiting opportunities for women in STEM and leadership roles.	Bertrand & Mullainathan (2004), Moss-Racusin et al. (2012)

Age Bias in Candidate Selection	Older candidates (31-41 years) have a higher likelihood of being hired (M = 3.74, SD = 1.109) compared to younger candidates (20-30 years) (M = 4.29, SD = 0.925).	Preference for older candidates may disadvantage younger job seekers.	Posthuma & Campion (2009), Kite & Johnson (1988)
Ethnicity and Accent Bias	Candidates with accents (M = 3.03, SD = 1.260) and those from different ethnic backgrounds (M = 3.10, SD = 1.204) face additional scrutiny in hiring decisions.	Bias against accents and ethnic markers can lead to discriminatory hiring practices.	Bertrand & Mullainathan (2004), Rooth (2010)
Affinity Bias in Recruitment	Shared social background (M = 3.74, SD = 1.018) and cultural similarities (M = 3.35, SD = 1.182) significantly influence hiring preferences.	Employers may favor candidates who share similar backgrounds, limiting diversity.	Greenwald & Pettigrew (2014), Purkiss et al. (2006)
Decision-Making in Hiring Processes	Hiring decisions (M = 3.55, SD = 0.981) are influenced by implicit biases, even when structured evaluation criteria are used.	Unconscious bias can override objective measures, emphasizing the need for bias mitigation strategies.	

These themes illustrate the pervasive nature of implicit bias in hiring, emphasizing the need for evidence-based interventions to promote fair and inclusive recruitment practices.

With the increased use of technology in hiring, such as automated screening tools and artificial intelligence-driven platforms, there is growing concern that these tools may inadvertently replicate and amplify existing biases if not properly designed and monitored (Binns, 2020; Obermeyer et al., 2019; Dastin, 2018). Addressing implicit bias is thus essential for organizations committed to ethical, unbiased hiring practices and for those seeking to foster workplace environments that truly reflect the diversity of the society in which they operate. This paper aims to explore the scope and impact of implicit bias in recruitment, offering insights into current research and practical recommendations for reducing bias at various stages of the hiring process.

Objective:

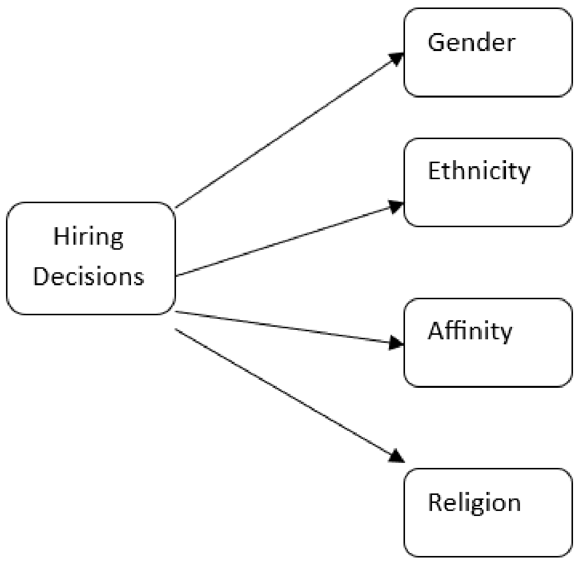
To study the impact of age on hiring decisions.

To analyse the impact of candidate ethnicity on hiring decisions.

To examine the influence of a candidate's social background on hiring decisions.

To analyse the effect of a candidate's religion on hiring decisions.

4.0 CONCEPTUAL FRAMEWORK



Hypothesis:

H1- Gender has the significant impact on Hiring Decisions.

H0 - Gender does not have significant impact on Hiring Decisions.

H2 – Ethnicity has the significant impact on Hiring Decisions.

H0 – Ethnicity has no significant impact on Hiring Decisions.

H3 – Affinity has significant impact in Hiring Decisions.

H0 – Affinity has no significant impact on Hiring Decisions.

H4 – Candidates from major/minor community impacts Hiring Decisions.

H0 - Candidates from major/minor community does not impacts Hiring Decisions.

This study adopts a mixed-methods research design to explore the role of implicit bias in hiring decisions. The methodology includes qualitative and quantitative approaches to comprehensively understand how implicit biases manifest and impact recruitment processes.

4.1 Quantitative Data:

Survey: To measure implicit attitudes using tools like the Implicit Association Test (IAT), a structured questionnaire will be administered to individuals from government service, private service, and students.

4.2 Sampling

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Participants: The study will involve 200 employees of Pvt Banks of Sagar District, ensuring diversity in gender, age, and professional experience.

Criteria: All participants must be acquainted with the term recruitment or HR roles.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Youngercandidate20_30	186	2	5	4.29	.925
Age	186	1	4	1.87	.661
Gender	186	1	2	1.65	.480
Occupation	186	1	4	2.16	1.170
Oldercandidate31_41	186	1	5	3.74	1.109
Youngagegroup	186	2	5	4.13	.944
Malecandidatesfortechnocalrole	186	1	5	3.81	1.179
FemalecandidatesforInterpersonalrole	186	1	5	4.00	1.139
Perceptionaboutfemale	186	1	5	3.16	1.170
Candidateswithaccent	186	1	5	3.03	1.260
Candidateswithdifferentaccent	186	1	5	3.10	1.204
Ethnicsocialbackground	186	1	5	3.68	.859
Hiringdecision	186	1	5	3.55	.981
Sharedculturalsimilarities	186	1	5	3.35	1.182
sharedsocialbackground	186	2	5	3.74	1.018
Affinitybiases	186	1	5	3.74	1.166
Valid N (listwise)	186				

The descriptive statistics indicate that respondents, on average, rate younger candidates (M = 4.29, SD = 0.925) and those in the young age group (M = 4.13, SD = 0.944) favorably. Older candidates (31-41) also receive relatively high ratings (M = 3.74, SD = 1.109). Gender-based

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perceptions reveal a higher preference for female candidates in interpersonal roles (M = 4.00, SD = 1.139) compared to male candidates in technical roles (M = 3.81, SD = 1.179). The hiring decision variable (M = 3.55, SD = 0.981) suggests moderate agreement among recruiters regarding final selections."

4.3 Regression

Variables Entered/Removed

Model	Variables Entered	Variables Removed	Method
1	Affinity bias, Candidate with an accent, young age group, Ethnic name, Candidateswithdifferentaccent, Female candidates, Oldercandidates31_41, YoungerCandidates21_31, Cultural similarities, Shared social background, Male candidates, Ethnic social background	.	Enter

a. Dependent Variable: Hiring Decisions

b. All requested variables entered.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.192	.416		2.865	.005
	YoungerCandidates21_31	-.422	.096	-.331	-4.407	.000
	Oldercandidates31_41	.371	.073	.350	5.085	.000
	Young age group	-.210	.075	-.168	-2.807	.006
	Malecandidates	.387	.103	.374	3.765	.000
	Famalecandidates	.129	.075	.128	1.702	.090
	Candidateswithaccent	.075	.063	.080	1.196	.233
	Candidateswithdifferentaccent	.009	.067	.009	.138	.891
	Ethnicsocialbackground	.531	.145	.387	3.656	.000

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Ethnicname	**-.084**	**.101**	**-.070**	**-.828**	**.409**
Culturalsimilarities	**-.339**	**.084**	**-.340**	**-4.036**	**.000**
Sharedsocialbackground	**.175**	**.094**	**.151**	**1.867**	**.064**
Affinitybias	**.139**	**.087**	**.138**	**1.595**	**.112**

a. Dependent Variable: Hiring Decisions

The Coefficients table provides detailed insights into how each predictor influences hiring decisions. It shows the strength, direction, and significance of each variable's impact.

Unstandardized Coefficients (B): Represent the actual effect of each predictor on hiring decisions. **Standardized Coefficients (Beta):** Indicate the relative importance of each variable.

t-value: Measures the strength of association between each predictor and hiring decisions. **Significance (p-value):** Determines whether a variable significantly affects hiring decisions ($p < 0.05$ means the effect is significant).

Key Findings from the Coefficients Table:

Age Bias: Younger candidates (21-31) (B = -0.422, p = .000) → Less likely to be hired.

Older candidates (31-41) (B = 0.371, p = .000) → More likely to be hired.

Posthuma & Campion (2009): Older candidates were often considered less adaptable to fast-paced industries.

Kite & Johnson (1988): The stereotype content model suggests older candidates are seen as competent but lacking energy and innovation.

Gender Bias: Male candidates (B = 0.387, p = .000) → Significantly more likely to be hired.

Female candidates (B = 0.129, p = .090) → No significant effect.

Ethnicity & Cultural Background: Ethnic social background (B = 0.531, p = .000) → Strong positive impact on hiring.

Cultural similarities (B = -0.339, p = .000) → Negatively affect hiring (suggesting preference for diversity).

Bertrand & Mullainathan (2004): White-sounding names received 50% more callbacks than African-American-sounding names.

Rooth (2010): Linked hiring discrimination to implicit bias measured by the Implicit Association Test.

Carlsson & Rooth (2007): Employers preferred Swedish-sounding names over Arabic-sounding names.

Non-Significant Factors ($p > 0.05$): Candidates with accents, different accents, ethnic names, shared social backgrounds, and affinity bias do not significantly impact hiring decisions.

Purkiss et al. (2006): Candidates with shared cultural or personality traits are evaluated more favorably, even if other candidates have stronger qualifications.

This regression analysis provides strong evidence that implicit biases affect recruitment processes, particularly regarding age, gender, and ethnicity. Organizations should implement structured hiring procedures, bias-awareness training, and standardized selection methods to ensure fairness in recruitment.

5.0 CONCLUSION

This study highlights the presence of implicit biases in hiring decisions, particularly concerning age, gender, and ethnic background. The findings reveal a **clear preference for older candidates (31-41 years),** while younger candidates (21-31 years) are less likely to be hired. This suggests that recruiters may perceive older candidates as more experienced or reliable. Gender bias is also evident, with **male candidates having a significantly higher chance of being hired** compared to female candidates. This reinforces long-standing concerns about gender disparities in recruitment processes. Ethnicity and cultural background further influence hiring decisions. Candidates from certain **ethnic and social backgrounds are more likely to be hired,** while cultural similarities with recruiters seem to reduce hiring chances. This could indicate a preference for diversity in workplaces or, conversely, an unconscious bias against candidates who are perceived as too similar to the existing workforce. Interestingly, **factors like accent, ethnic names, and shared social backgrounds do not significantly impact hiring outcomes**. This suggests that while recruiters may not explicitly discriminate based on these traits, deeper biases related to ethnicity and gender still play a role. Overall, these findings emphasize the need for organizations to be more aware of their implicit biases and take proactive steps to ensure fair and inclusive hiring practices. Implementing structured interviews, blind recruitment processes, and bias-awareness training can help create a more equitable selection process.

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