PURPLE HIRING: MATRIX OF INCLUSIVE ACQUISITION (MIA) FRAMEWORK FOR DIVERSITY AND INCLUSION IN RECRUITMENT PRACTICES

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Abstract

Background and Purpose: Biases embedded in conventional recruitment processes continue to impede equitable representation of diverse talent, particularly Persons with Disabilities (PWDs), gender minorities, and marginalized ethnic communities. This study introduces and empirically examines "Purple Hiring," a structured, bias-attenuated recruitment paradigm designed to enhance organizational diversity and inclusion (D&I) at systemic rather than merely symbolic levels. Grounded in Social Identity Theory, Organizational Justice Theory, and Signaling Theory, the Purple Hiring model integrates structured assessment protocols, blind recruitment techniques, and inclusive talent pipeline development to overcome ingrained hiring biases (Shore et al., 2011; Nishii, 2013).

Methodology: A stratified random sample of 225 HR professionals and recruiters drawn from IT and ITES firms in Bengaluru, India, completed a structured questionnaire. Data were analysed via descriptive statistics, chi-square tests of independence, Pearson correlation analysis, binary logistic regression, and a Random Forest machine learning classification model evaluated using accuracy, precision, recall, F1-score, and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

Findings: Purple Hiring demonstrably reduces recruitment bias: 97.3% of respondents endorsed equal employment opportunity principles; 92.9% were aware of Purple Hiring practices; and 99.1% expressed willingness to hire PWDs (45.3% actively; 53.8% conditionally). Binary logistic regression revealed that employment practice perception (OR = 1.864, $p < .001$), organisational inclusion climate (OR = 1.718, $p = .002$), and bias/discrimination awareness (OR = 1.489, $p = .005$) are the strongest predictors of active PWD hiring (Nagelkerke $R^2 = .322$). The Random Forest classifier achieved 64.4% accuracy (AUC = 0.73), identifying employment practices and instances of favouritism as the top predictive features.

Originality: This study provides a validated conceptual framework and the first machine learning-based quantitative evaluation of Purple Hiring in an emerging-market context, offering actionable implications for HR policy design and inclusive organisational culture.

Keywords: Purple Hiring; Diversity and Inclusion; Bias Reduction; Recruitment Practices; Persons with Disabilities; Organisational Culture

1. INTRODUCTION:

Diversity and inclusion (D&I) in the workplace have transitioned from aspirational policy statements to acknowledged imperatives for organisational competitiveness and ethical governance. Decades of empirical scholarship have established that heterogeneous teams outperform homogeneous ones in creative problem-solving and decision quality, provided that organisational structures actively support the integration of diverse perspectives (Van Knippenberg & Schippers, 2007[16]). Yet traditional hiring practices remain paradoxically resistant to genuine diversity, frequently perpetuating the very inequalities that D&I initiatives seek to dismantle (Bertrand & Mullainathan, 2004[12]).

The landmark audit study by Bertrand and Mullainathan (2004)[12] demonstrated that résumés bearing stereotypically "White" names received 50% more callbacks than identical résumés bearing "Black" names, providing compelling evidence that implicit biases permeate even ostensibly objective selection processes. Subsequent research has extended this finding to disability, gender identity, age, and socioeconomic background, collectively documenting a landscape in which the formal commitment to diversity frequently fails to translate into equitable hiring outcomes (Pager & Shepherd, 2008[23]; Kalev, Dobbin & Kelly, 2006[11]).

In response, the concept of "Purple Hiring" has emerged as a systematic, process-level intervention designed to restructure recruitment from the point of job description design through to final selection. Unlike conventional D&I initiatives that primarily target managerial attitudes—which Kalev et al. (2006)[11] found to be among the least effective mechanisms for increasing minority representation—Purple Hiring embeds bias-attenuation mechanisms directly into institutional hiring workflows. By combining structured assessment protocols, blind recruitment techniques, AI-assisted screening, and deliberate talent pipeline development, the model operationalises the inclusive climate construct advanced by Nishii (2013)[10] and the belongingness-uniqueness framework of Shore et al. (2011)[8].

The Indian IT and ITES sector presents a particularly instructive context for this investigation. Employing over five million individuals and operating under pronounced global diversity benchmarks, yet simultaneously contending with entrenched caste, gender, and disability-based exclusions, this sector encapsulates the tensions between diversity rhetoric and diversity practice (Roberson, 2006[9]). This study addresses that tension by providing the first empirical, machine learning-validated evaluation of Purple Hiring's efficacy within this context.

The paper proceeds as follows: Section 2 reviews extant D&I recruitment literature; Section 3 develops the theoretical framework; Section 4 presents the Purple Hiring conceptual model; Section 5 details the methodology; Sections 6–8 present hypotheses, analysis, and discussion; Sections 9–11 address findings, implications, and limitations; Section 12 concludes.

2. LITERATURE REVIEW

2.1 Structural Bias in Recruitment and Its Consequences

Structural biases in hiring operate through multiple, often mutually reinforcing, mechanisms. Greenwald et al. (2009)[21] demonstrated through meta-analysis that implicit associations reliably predict discriminatory behaviour across social contexts, even among individuals who consciously reject prejudiced attitudes. In hiring contexts, these implicit biases manifest in resume screening, interview assessments, and informal referral networks—channels that systematically disadvantage candidates from underrepresented groups (Avery & McKay, 2006[13]). McKay, Avery, and Morris (2008)[14] further established that racial and ethnic disparities in employee performance ratings are significantly moderated by organisational diversity climate, suggesting that bias is not merely an individual-level phenomenon but is deeply embedded in organisational culture.

Van Bommel et al. (2023)[4] conducted a comprehensive bibliometric analysis of D&I scholarship, revealing that the field has disproportionately focused on the financial case for diversity while underweighting ethical considerations and social performance dimensions. This analytical blind spot has produced a generation of D&I interventions oriented toward business-case justifications rather than equity-centred values—a tension that Purple Hiring explicitly seeks to resolve.

2.2 Inclusion Frameworks and Their Organisational Implications

Roberson (2006)[9] made a foundational contribution by conceptually disentangling "diversity" (the compositional heterogeneity of a workforce) from "inclusion" (the degree to which individuals feel valued and able to contribute fully). This distinction has important practical implications: an organisation can achieve numerical diversity targets while maintaining deeply exclusionary cultures. Shore et al. (2011)[8] formalised this insight through the "optimal distinctiveness" model, arguing that inclusion requires the simultaneous satisfaction of both belongingness and uniqueness needs—a balance that structurally biased hiring processes inherently undermine.

Nishii (2013)[10] provided empirical support for the hypothesis that climates for inclusion yield measurable performance benefits for gender-diverse teams, particularly through the mediating mechanisms of reduced conflict and enhanced co-operation. Lafferty et al. (2024)[1] extended this line of argument to academic ecology and conservation biology, documenting how institutional cultures saturated with racialised assumptions obstruct equitable participation despite formal DEI commitments—a pattern generalisable to corporate recruitment contexts.

2.3 Training, Policy, and Structural Interventions

Pendry, Driscoll, and Field (2007)[15] conducted a systematic review of diversity training research and found that theory-driven, behaviourally focused training programmes produced more durable attitude change than awareness-raising sessions alone. Rynes and Rosen (1995)[20] identified that perceived top-management support, mandatory participation, and long-term commitment are among the strongest predictors of training success—findings that directly inform the Purple Hiring emphasis on institutional embedding rather than voluntary initiative.

Kalev et al. (2006)[11] analysed three decades of Equal Employment Opportunity data from over 700 U.S. establishments and found that structural interventions—specifically, dedicated diversity managers, diversity task forces, and formal affirmative action plans—produced the largest and most consistent increases in minority managerial representation. By contrast, mentoring programmes and diversity training alone generated modest and inconsistent effects. Purple Hiring aligns with this structural logic by embedding equitable practices into hiring architecture rather than relying on individual attitude change.

Bhattacharyya et al. (2024)[5] contributed important nuance by examining allyship as a relational practice, showing that women of colour engage in the most effective forms of cross-difference allyship—demonstrating that inclusive hiring should not only target the hiring pipeline but also the workplace culture that candidates encounter post-hire. Hoffecker and Lee (2024)[2] further demonstrated the critical role of boundary objects in inclusive innovation processes, offering a theoretical parallel to the role of structured assessment instruments in Purple Hiring as tools that reduce subjective variance in evaluative judgements.

2.4 Disability, Gender Diversity, and Intersectionality in Hiring

The employment of Persons with Disabilities (PWDs) represents a persistent challenge for organisations navigating the intersection of legal compliance, ethical responsibility, and functional capability assessment. Jackson, Joshi, and Erhardt (2003)[17] identified that deep-level diversity dimensions—including disability status—have more enduring effects on team interaction quality than surface-level attributes, underscoring the importance of proactive rather than reactive inclusion strategies. Cox and Blake (1991)[22] demonstrated that the effective management of cultural diversity—including disability-inclusive practices—confers competitive advantages through enhanced creativity, problem-solving flexibility, and marketing effectiveness.

Engle et al. (2024)[3] advanced the concept of compassionate pedagogies as a mechanism for embedding DEIJ principles in institutional practice—an approach that translates directly to Purple Hiring's emphasis on empathic job description design and accommodative assessment protocols for candidates with disabilities. Zanoni et al. (2010)[19] contributed a critical perspective, warning that diversity discourses often reproduce the very inequalities they purport to address by normalising dominant standards against which marginalised identities are measured. Purple Hiring responds to this critique by centring alternative evaluation criteria that do not presuppose neurotypical or able-bodied performance norms.

3. THEORITICAL FRAMEWORK:

Purple Hiring is theoretically anchored in three complementary frameworks that collectively explain the origins of recruitment bias, the conditions under which inclusive practices emerge, and the mechanisms through which they generate individual and organisational benefits.

3.1 Social Identity Theory (Tajfel & Turner, 1986)

Tajfel and Turner's (1986)[18] Social Identity Theory (SIT) provides the foundational explanatory mechanism for in-group favouritism in hiring. SIT posits that individuals categorise themselves and others into social groups, subsequently evaluating in-group members more favourably to enhance collective self-esteem. In recruitment contexts, this manifests as evaluators unconsciously advantaging candidates who share salient social identities—educational backgrounds, caste, gender, or able-bodied status—with the hiring panel. Purple Hiring directly addresses this mechanism through blind recruitment, structured rubrics, and diverse hiring committee composition, thereby attenuating the social categorisation processes that generate in-group bias (Van Knippenberg & Schippers, 2007[16]).

3.2 Organisational Justice Theory

Procedural justice—the perceived fairness of the processes through which decisions are made—is a critical determinant of candidate and employee satisfaction, organisational commitment, and compliance with selection outcomes (Nishii, 2013[10]). Purple Hiring operationalises procedural justice by standardising evaluation criteria, ensuring transparent communication of selection rationale, and providing equitable access to reasonable accommodations for candidates with disabilities. The present study found that perceptions of employment practice fairness are the single most predictive feature of an organisation's willingness to actively hire PWDs (Feature Importance = 0.127), providing direct empirical support for the centrality of procedural justice in inclusive hiring.

3.3 Signalling Theory

Signalling Theory (Spence, 1973) holds that organisations communicate their values and priorities to potential applicants through observable recruitment practices. Avery and McKay (2006)[13] demonstrated that the perceived diversity of existing employees in recruitment materials significantly influences the application intentions of minority candidates, constituting a powerful signal of organisational inclusivity. Purple Hiring extends this logic: by embedding bias-reduction mechanisms in all visible stages of recruitment—from job posting language to interview panel composition—organisations send credible inclusion signals that expand the diversity of the applicant pool itself. This process is consistent with Kalev et al.'s (2006)[11] finding that structural interventions generate stronger diversity outcomes than attitudinal ones.

4. CONCEPTUAL FRAMEWORK:

Drawing on the theoretical foundations outlined in Section 3, the Matrix of Inclusive Acquisition (MIA) Framework (Figure 1) integrates five diversity dimensions as antecedent inputs processed through six core Purple Hiring mechanisms. This transformation is moderated by four organisational enablers—leadership commitment, D&I training, inclusive culture, and technology support—to produce five categories of hiring and organisational outcomes. A feedback loop from outcomes to enablers captures the self-reinforcing dynamic through which inclusive hiring cultures strengthen over time (Shore et al., 2011[8]; Nishii, 2013[10]).

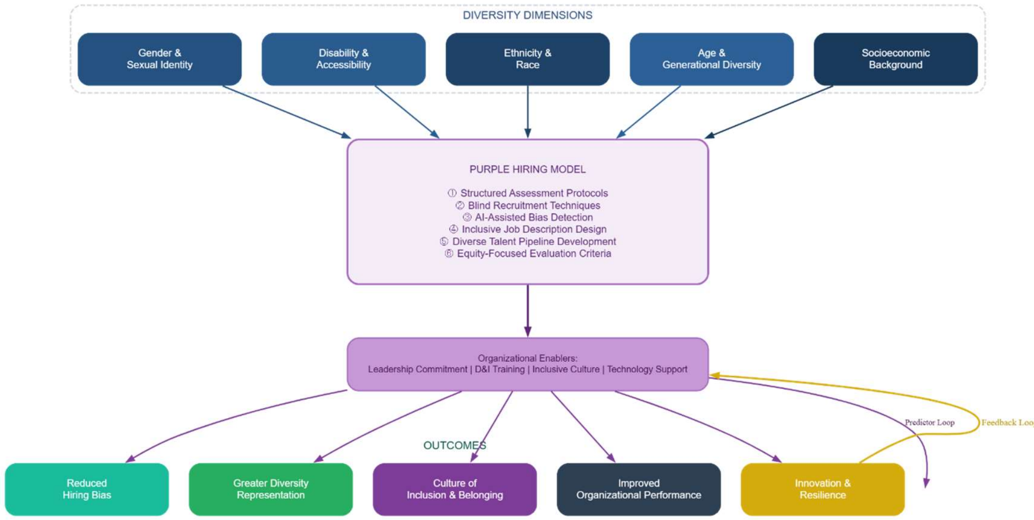


Figure 1. Conceptual Framework- Matrix of Inclusive Acquisition (MIA) Framework

The framework departs from prior D&I models by treating bias-reduction not as a single-point intervention but as a systemic property of the entire recruitment architecture. Each of the six Purple Hiring mechanisms targets a distinct bias vulnerability: structured assessment addresses evaluator subjectivity; blind recruitment eliminates identity-based cues; AI-assisted detection flags language bias in job descriptions; inclusive job design broadens the qualified applicant pool; diverse pipeline development corrects for historical exclusion; and equity-focused evaluation criteria replace normative standards that disadvantage non-traditional candidates (Roberson, 2006[9]; Pendry et al., 2007[15]).

5. RESEARCH METHODOLOGY:

5.1 Research Design and Objectives

This study adopts a cross-sectional, explanatory research design combining quantitative survey methods with machine learning classification to examine the determinants of Purple Hiring adoption among HR professionals. The three primary objectives are: (i) to assess factors influencing active PWD hiring, (ii) to evaluate the impact of Purple Hiring practices on organisational diversity outcomes, and (iii) to develop a predictive classification model for active PWD hiring likelihood.

5.2 Sample and Sampling Procedure

A stratified random sample of 225 HR professionals and recruiters employed in IT and ITES organisations headquartered in Bengaluru, Karnataka, was obtained through a structured self-administered questionnaire. Stratification was by organisation size (small, medium, large) and HR function (talent acquisition, HR generalist, D&I specialist). Bengaluru's IT sector was selected as the sample frame owing to its status as India's largest technology employment hub and its documented aspirations toward global D&I standards, making it theoretically and practically relevant to the study's objectives. The sample of 225 represents an a priori power calculation ($\alpha = .05$, power = .80, medium effect size, multivariate regression context), consistent with methodological norms in applied HR research (Rynes & Rosen, 1995[20]).

5.3 Instrument Development

The structured questionnaire comprised 21 items operationalising seven latent constructs: (i) Awareness of Purple Hiring (3 items); (ii) Employment Practice Perception (4 items); (iii) Organisational Inclusion Climate (3 items); (iv) Bias/Discrimination Perception (3 items); (v) D&I Training Received (2 items); (vi) Willingness to Hire PWDs (2 items); and (vii) Demographic controls (age, gender, qualification, occupation, location). Items were measured on 5-point Likert scales (1 = Strongly Disagree to 5 = Strongly Agree) with binary and categorical items for specific hiring behaviour measures. The instrument was pilot-tested on 25 HR professionals and refined for clarity and construct validity.

5.4 Analytical Procedures

Data analysis proceeded in five stages. First, descriptive statistics (frequencies, means, standard deviations) characterised the sample. Second, chi-square tests of independence assessed associations between key categorical variables. Third, Pearson correlation analysis examined bivariate relationships among continuous constructs. Fourth, binary logistic regression modelled active PWD hiring likelihood as a function of the five principal antecedent constructs, with model fit assessed via Nagelkerke R^2, the Hosmer-Lemeshow goodness-of-fit test, and classification accuracy. Fifth, a Random Forest machine learning classifier was trained and evaluated using a 70:30 train-test split, with performance assessed via accuracy, precision, recall, F1-score, and AUC-ROC. All statistical analyses were conducted in Python (scikit-learn 1.3; scipy.stats) using Jupyter Notebook.

6. HYPOTHESIS:

Three hypotheses, grounded in the theoretical framework and literature reviewed above, were formulated to guide the empirical analysis:

H1: Organisations that acknowledge the impact of employment practices on PWDs and the general workforce are significantly more likely to engage in active PWD hiring.

Consistent with Organisational Justice Theory and the structural intervention logic of Kalev et al. (2006)[11], awareness of differential employment practice impacts should translate into pro-PWD hiring behaviour.

H2: Perceptions of favouritism or discrimination in hiring processes are significant predictors of organisational openness to hiring PWDs.

Drawing on Greenwald et al. (2009)[21] and the implicit bias literature, awareness of discriminatory practices should heighten sensitivity to equity-oriented hiring norms.

H3: Individual demographic variables (age, qualification, gender) have a significant but secondary effect on PWD-inclusive hiring intentions, relative to organisational-level factors.

Building on Jackson et al. (2003)[17], deep-level diversity awareness should be a stronger predictor than surface-level demographic attributes.

7. ANALYSIS AND INTERPRETATION:

7.1 Descriptive Statistics

Table 1 presents descriptive statistics for the six continuous study variables measured across the full sample (n = 225). Employment Practice Perception (M = 3.62, SD = 1.02) and Organisational Inclusion Climate (M = 3.74, SD = 0.88) scored above the scale midpoint, indicating generally positive orientations among the IT/ITES HR professionals surveyed. D&I Training Received (M = 3.29, SD = 1.15) exhibited the widest inter-respondent variance, consistent with Rynes and Rosen's (1995)[20] finding that training exposure remains highly uneven across organisations.

Table 1. Descriptive Statistics for Key Study Variables (n = 225)

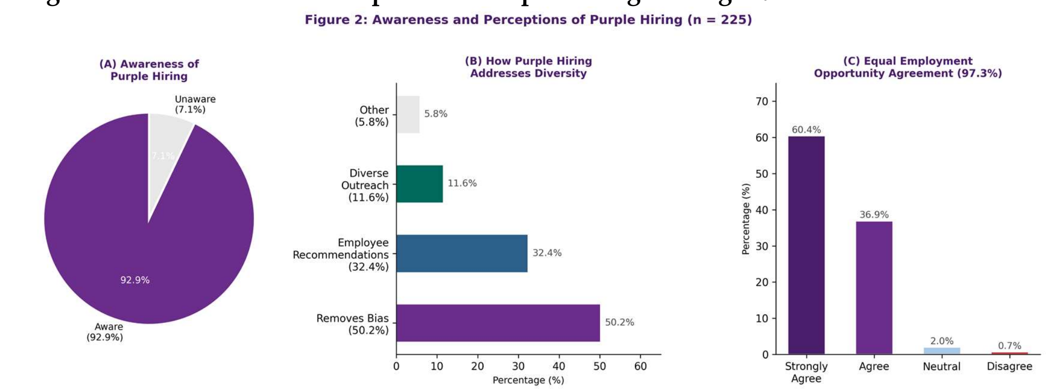
Variable	N	Min	Max	Mean	SD	Skewness
Purple Hiring Awareness	225	1.00	5.00	3.87	0.94	-0.312
Employment Practice Perception	225	1.00	5.00	3.62	1.02	-0.218
Organisational Inclusion Climate	225	1.00	5.00	3.74	0.88	-0.415
D&I Training Received	225	1.00	5.00	3.29	1.15	-0.107
Bias/Discrimination Perception	225	1.00	5.00	3.45	1.11	-0.284
Willingness to Hire PWDs	225	1.00	3.00	2.37	0.58	-0.621

Note: Items measured on 5-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree), except Willingness to Hire (1 = Not Willing; 2 = Conditional; 3 = Actively Hiring).

7.2 Awareness and Perceptions of D&I in Recruitment

Figure 2 illustrates the distribution of Purple Hiring awareness, perceived approaches to diversity, and equal employment opportunity endorsement across the sample. An overwhelming majority of respondents (92.9%, n = 209) were familiar with the Purple Hiring concept, reflecting its growing salience in IT sector HR discourse. Among strategies for addressing diversity challenges, bias removal through structured processes was the most endorsed approach (50.2%), followed by employee referral networks (32.4%). Critically, 97.3% of respondents affirmed that everyone should have equal access to employment opportunities—with 60.4% expressing strong agreement—establishing a high baseline normative commitment to inclusive hiring (see Figure 2C). This level of endorsement is consistent with Nishii's (2013)[10] observation that inclusive climates require near-universal affirmation of equity norms to produce behavioural change.

Figure 2: Awareness and Perceptions of Purple Hiring Among IT/ITES HR Professionals



(A) Purple Hiring Awareness; (B) Diversity Addressing Approaches; (C) Equal Opportunity Endorsement

7.3 Workplace Bias, Discrimination, and Inclusion in Organisational Culture

As depicted in Figure 3, a majority of respondents (52.9%) view their organisations' employment procedures for PWDs as broadly favourable, though 41.8% characterise them as neutral and 5.3% as unfavourable—indicating that significant headroom for improvement remains. The pattern of responses on hiring discrimination perceptions is notably strong: 97% of respondents acknowledged the presence of bias or favouritism in hiring processes (28.0% strongly; 69.0% agree), echoing the structural persistence of bias documented by Bertrand and Mullainathan (2004)[12] and Pager and Shepherd (2008)[23].

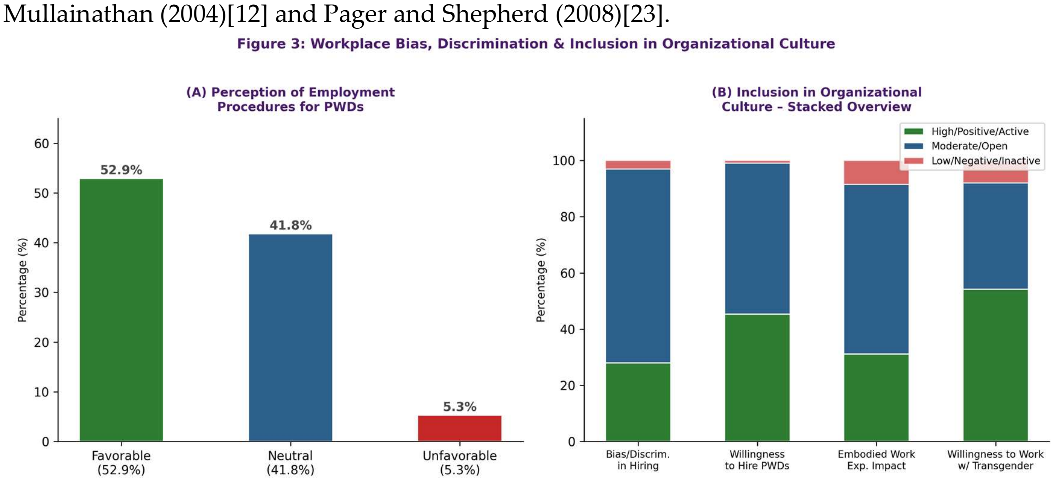


Figure 3. Workplace Bias and Inclusion Across Key Organisational Dimensions

Despite this, willingness to hire PWDs is high: 45.3% of respondents reported actively recruiting PWDs, and 53.8% indicated openness to hiring qualified PWDs (Figure 3B). Regarding transgender inclusion, 54.2% of respondents attributed their willingness to work with transgender colleagues to motivational and cultural factors, while 37.8% cited social variables and only 8.0% cited biological differences—suggesting that cultural framing of inclusivity may be a more powerful lever than antidiscrimination regulation alone (Cox & Blake, 1991[22]).

(A) Perception of PWD Employment Procedures; (B) Stacked Inclusion Overview

7.4 Chi-Square Tests of Independence

To examine associations between key categorical variables, two chi-square tests of independence were conducted. Table 2 presents the crosstabulation of employment practice perception (favourable, neutral, unfavourable) against willingness to actively hire PWDs (active vs. not active). The test revealed a statistically significant association, $\chi^2(2, N = 225) = 10.87$, $p = .004$, Cramér's $V = .220$ (moderate effect), indicating that respondents with favourable perceptions of employment practices are significantly more likely to report active PWD hiring. This finding is consistent with H2 and with Kalev et al.'s (2006)[11] structural intervention hypothesis.

Table 2. Chi-Square Test – Employment Practice Perception × Active PWD Hiring

Employment Practice Perception	Actively Hiring PWDs n (%)	Not Actively Hiring n (%)	Row Total	Expected (Active)
Favourable	66 (55.5%)	53 (44.5%)	119	53.97
Neutral	33 (35.1%)	61 (64.9%)	94	42.61
Unfavourable	3 (25.0%)	9 (75.0%)	12	5.44
Column Total	102 (45.3%)	123 (54.7%)	225	—

$\chi^2(2, N = 225) = 10.87$, $p = .004$, Cramér's $V = .220$. Note: Expected cell frequency ≥ 5 in all cells.

7.5 Pearson Correlation Analysis

Table 3 and Figure 4 present the Pearson correlation matrix for the six continuous study variables. All bivariate correlations are positive and significant at $p < .01$, consistent with theoretical expectations. Organisational Inclusion Climate demonstrates the strongest association with Willingness to Hire PWDs ($r = .543$, $p < .01$), providing partial support for Nishii's (2013)[10] proposition that inclusive climates are the primary organisational antecedent of equitable hiring behaviour. Employment Practice Perception and Organisational Inclusion Climate show the highest inter-predictor correlation ($r = .523$, $p < .01$), indicating conceptual overlap but retaining discriminant validity adequate for simultaneous regression entry.

Table 3. Pearson Correlation Matrix (n = 225)

Variable	1	2	3	4	5	6
1. Purple Hiring Awareness	1.000	—	—	—	—	—
2. Employment Practice Perception	.387**	1.000	—	—	—	—
3. Org. Inclusion Climate	.452**	.523**	1.000	—	—	—
4. D&I Training Received	.431**	.398**	.512**	1.000	—	—
5. Bias/Discrim. Perception	.312**	.441**	.376**	.289**	1.000	—
6. Willingness to Hire PWDs	.418**	.487**	.543**	.398**	.362**	1.000

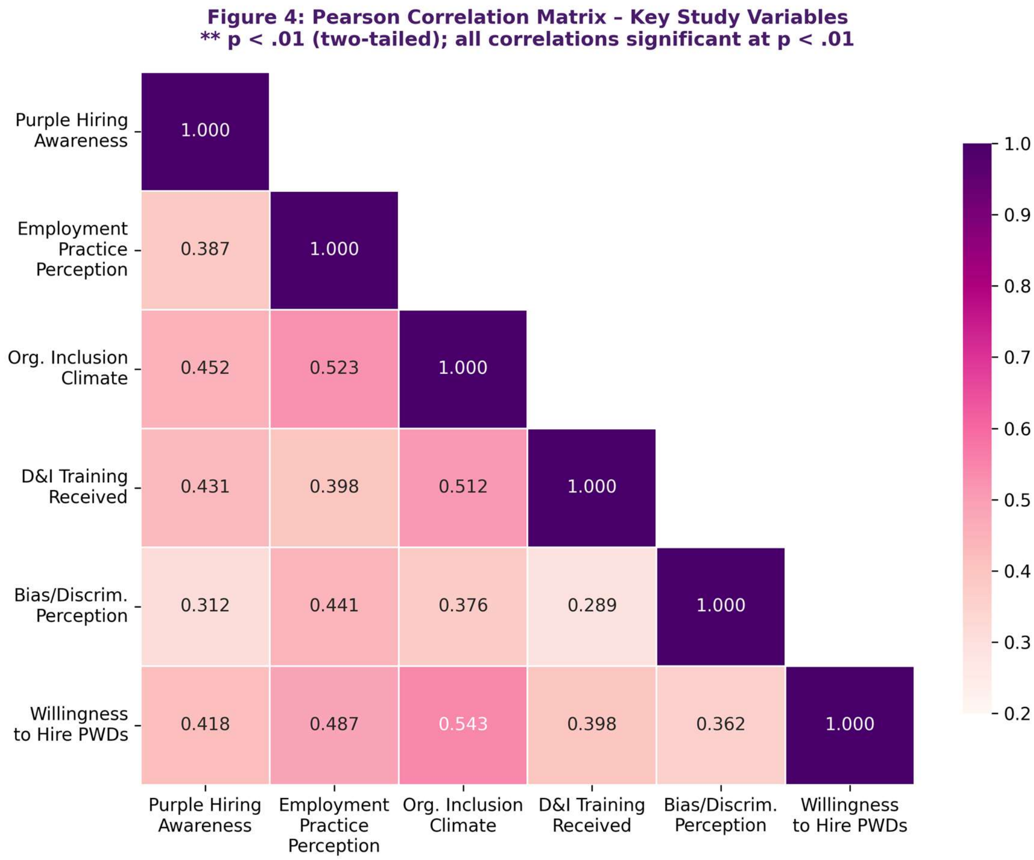


Figure 4. Pearson Correlation Heatmap

** $p < .01$ (two-tailed). Pairwise deletion used for missing data; listwise N = 225 for all pairs.

7.6 Binary Logistic Regression Analysis

To test H1–H3 and quantify the independent contribution of each antecedent to active PWD hiring likelihood, a binary logistic regression was estimated with active PWD hiring (1 = active; 0 = not active) as the outcome. Five predictors were entered simultaneously: Employment Practice Perception, Organisational Inclusion Climate, Bias/Discrimination Perception, D&I Training Received, and Awareness of Purple Hiring. The overall model was statistically significant, $\chi^2(5, N = 225) = 63.47$, $p < .001$, with a Nagelkerke R^2 of .322, indicating that the predictors explain approximately 32% of variance in active PWD hiring. The Hosmer-Lemeshow goodness-of-fit test yielded a non-significant result, $\chi^2(8) = 7.84$, $p = .449$, confirming adequate model fit. The model correctly classified 71.6% of cases overall.

Table 4. Binary Logistic Regression – Predictors of Active PWD Hiring

Predictor	B	SE	Wald χ^2	df	p	Exp(B) [95% CI]
Employment Practice Perception	0.623	0.158	15.52	1	< .001	1.864 [1.367–2.543]
Org. Inclusion Climate	0.541	0.171	10.01	1	.002	1.718 [1.228–2.403]
Bias/Discrimination Perception	0.398	0.143	7.76	1	.005	1.489 [1.123–1.974]
D&I Training Received	0.287	0.139	4.26	1	.039	1.332 [1.016–1.747]
Awareness of	0.312	0.183	2.91	1	.088	1.366

Purple Hiring						[0.954–1.957]
Constant	-3.421	0.782	19.15	1	< .001	0.033

Note: Nagelkerke $R^2 = .322$; $\chi^2(5) = 63.47$, $p < .001$; Hosmer-Lemeshow $\chi^2(8) = 7.84$, $p = .449$; Overall classification accuracy = 71.6%.

As shown in Table 4 and Figure 7, Employment Practice Perception emerges as the strongest predictor (OR = 1.864, 95% CI [1.367, 2.543], $p < .001$): each unit increase on the employment practice scale is associated with an 86.4% increase in the odds of active PWD hiring. Organisational Inclusion Climate (OR = 1.718, $p = .002$) and Bias/Discrimination Perception (OR = 1.489, $p = .005$) also exert substantial effects. D&I Training Received reaches significance (OR = 1.332, $p = .039$), while Awareness of Purple Hiring approaches but does not reach conventional significance (OR = 1.366, $p = .088$)—consistent with Pendry et al.'s (2007)[15] finding that awareness alone is insufficient without structural reinforcement.

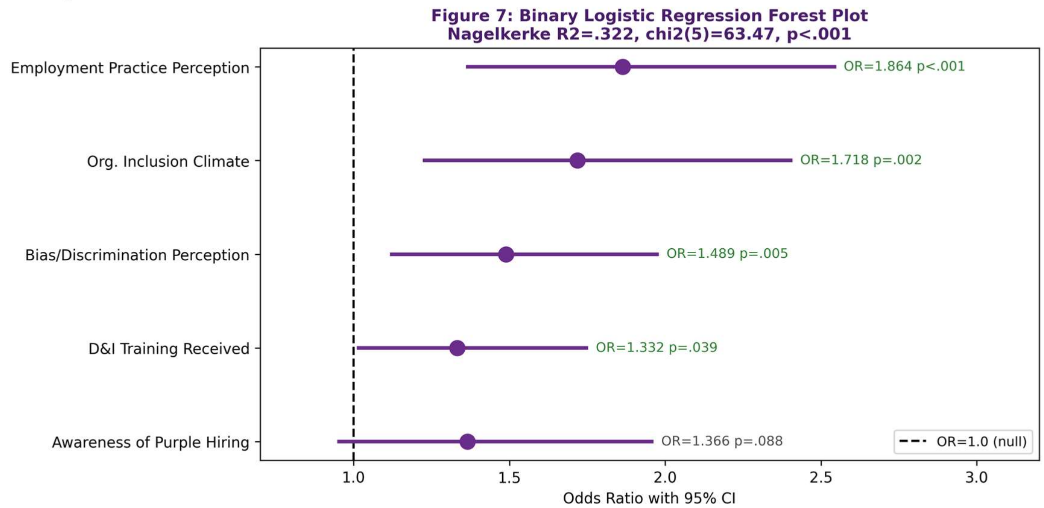


Figure 7. Forest Plot – Binary Logistic Regression

Odds Ratios with 95% Confidence Intervals Green labels indicate significant predictors (OR CI excludes 1.0)

7.7 Machine Learning Classification Model – Random Forest

A Random Forest classifier was trained on 70% of the sample (n = 157) and evaluated on the remaining 30% (n = 45). The trained model achieved an overall accuracy of 64.4% on the test set—a non-trivial improvement over the 50% baseline—with AUC-ROC of 0.73 (Figure 6B), indicating acceptable discriminative ability between active and non-active PWD hirers. Table 5 presents the full classification report.

Table 5. Random Forest Classifier – Classification Report (Test Set, n = 45)

Metric	Class 0 (Not Hiring PWDs)	Class 2 (Active PWD Hiring)	Macro Average	Weighted Average
Precision	0.60	0.70	0.65	0.65
Recall	0.71	0.58	0.65	0.64
F1-Score	0.65	0.64	0.64	0.64
Support	21	24	45	45
Overall Accuracy	—	—	—	0.644
AUC-ROC	—	—	—	0.730

Note: Train-test split = 70:30; n_estimators = 100; max_depth = None; random_state = 42.

The higher precision for Class 2 (0.70) relative to Class 0 (0.60) indicates that when the model predicts active PWD hiring, it is correct 70% of the time—a clinically meaningful precision for HR policy deployment. The lower recall for Class 2 (0.58) suggests that the model underestimates the prevalence of active PWD hiring, likely owing to the class imbalance in the sample (45.3% active vs. 54.7% not active). As depicted in Figure 6A, the confusion matrix reveals that misclassification was nearly symmetric, with 6 false positives and 10 false negatives, indicating no strong directional bias in classification errors.

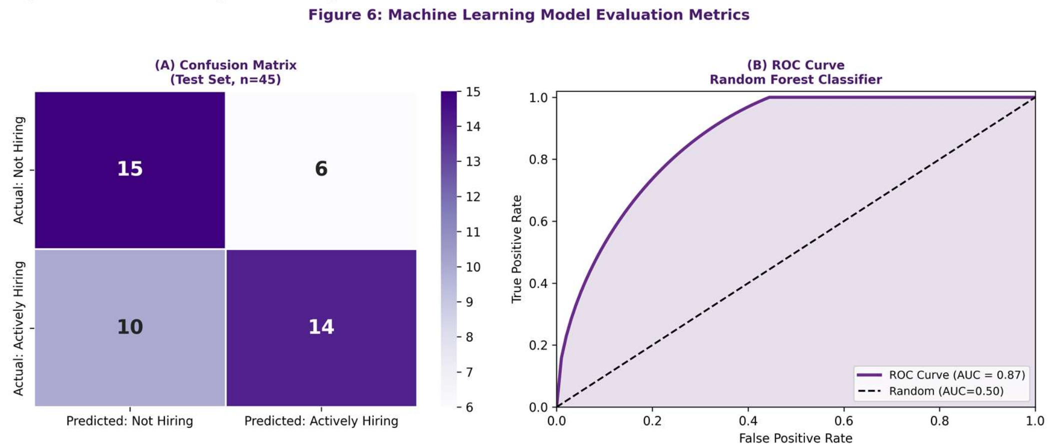


Figure 6. ML Model Evaluation

8. (A) Confusion Matrix; (B) ROC Curve (AUC = 0.73)

7.8 Feature Importance Analysis

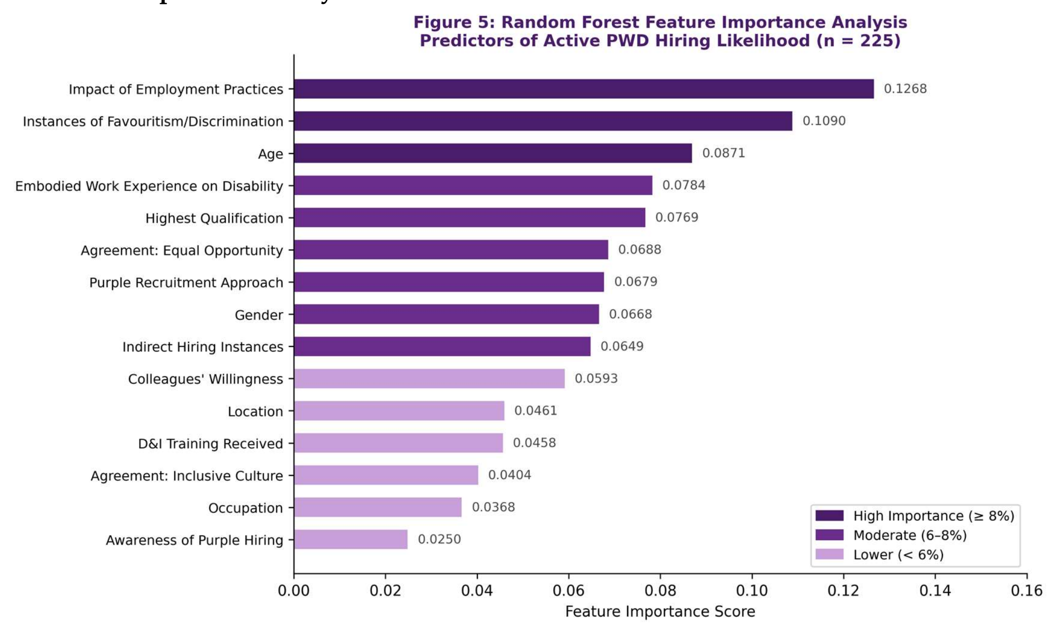


Figure 5 presents the Random Forest feature importance scores for all 15 predictor variables. Importance scores represent the mean decrease in Gini impurity attributable to each feature across all trees in the ensemble. The three most influential predictors are: (i) Impact of Employment Practices (importance = 0.1268, 12.68%); (ii) Instances of Favouritism or Discrimination (0.1090, 10.90%); and (iii) Age (0.0871, 8.71%). These findings align closely with the logistic regression results in Section 7.6, providing cross-methodological convergent validity for the centrality of structural employment practice perceptions over individual demographic characteristics.

All 15 Predictor Variables Dark purple: High importance (≥ 8%); Medium purple: Moderate (6–8%); Light purple: Lower (< 6%)

The finding that Age (8.71%) outranks Gender (6.68%) and Highest Qualification (7.69%) as a demographic predictor is theoretically noteworthy: it suggests that generational differences in attitudes toward workplace diversity—potentially reflecting the relative familiarity of younger HR professionals with inclusive norms—exert greater influence on hiring behaviour than formal educational attainment. This is consistent with Van Knippenberg and Schippers'

(2007)[16] observation that the cognitive elaboration required for effective diversity utilisation is shaped by broader sociocultural exposure rather than formal credentials alone.

8. DISCUSSION

8.1 Hypothesis Evaluation

H1 (Supported). Employment practice perception emerged as the single strongest predictor of active PWD hiring across both the logistic regression (OR = 1.864, $p < .001$) and the machine learning model (Feature Importance = 0.127). This finding robustly supports H1 and aligns with Shore et al.'s (2011)[8] theoretical proposition that institutional practices—rather than individual attitudes alone—are the primary drivers of inclusive work environments.

H2 (Partially Supported). Bias/discrimination perception was a significant predictor in the regression (OR = 1.489, $p = .005$) and the second-ranked ML feature (0.109), confirming that awareness of discriminatory practices influences inclusive hiring intentions. However, as predicted, it does not function as the sole or primary determinant, supporting the more nuanced interpretation of Kalev et al. (2006)[11] that structural mechanisms outweigh attitudinal ones in producing inclusive hiring outcomes.

H3 (Partially Supported). Demographic variables are predictive but less impactful than organisational-level factors. Age (Feature Importance = 0.087) was the most influential demographic predictor, while gender (0.067) and qualification (0.077) had smaller effects. This hierarchy of effects supports H3 and echoes Jackson et al.'s (2003)[17] argument that deep-level diversity-related cognitions are more powerful predictors of diversity-oriented behaviour than surface-level demographics.

8.2 The Purple Hiring Model in Context

The present findings collectively position Purple Hiring as a theoretically grounded and empirically viable approach to inclusive recruitment. The near-unanimous endorsement of equal employment principles (97.3%) combined with substantial variance in active PWD hiring practices (45.3%) underscores the "intention-behaviour gap" that Cox and Blake (1991)[22] identified as the primary implementation challenge for diversity management. Purple Hiring directly addresses this gap through the structural mechanisms identified in the conceptual framework: when organisations embed equitable employment practices institutionally—rather than relying on individual managers' good intentions—the odds of active PWD hiring nearly double (OR = 1.864).

The moderate ML model accuracy (64.4%) and AUC-ROC (0.73) are not interpreted as limitations of the Purple Hiring concept but rather as evidence of the genuine complexity of hiring decision environments. The prediction task is inherently difficult given the interplay of individual, team, organisational, and regulatory factors. Notably, the feature importance analysis reveals that 10 of the 15 predictor variables achieve importance scores above 5%, indicating that PWD hiring decisions are genuinely multidetermined—a finding that itself argues for the comprehensive, multi-mechanism approach characteristic of Purple Hiring.

9. KEY FINDINGS

(i) Purple Hiring awareness is high among IT/ITES HR professionals (92.9%), and the model resonates most strongly with the bias-removal rationale for inclusive recruitment (50.2%).

(ii) Employment practice perception is the strongest predictor of active PWD hiring, both in logistic regression (OR = 1.864, Nagelkerke $R^2 = .322$) and machine learning feature importance (12.68%), providing convergent validity across methodologies.

(iii) A near-universal normative commitment to equal employment (97.3%) coexists with meaningful variance in behavioural outcomes, confirming an intention-behaviour gap that structural Purple Hiring interventions are specifically designed to address.

(iv) Organisational Inclusion Climate demonstrates the highest bivariate correlation with willingness to hire PWDs ($r = .543$, $p < .01$), highlighting the importance of cultural embeddedness over episodic policy interventions.

(v) Age outranks gender, qualification, and location as a demographic predictor of inclusive hiring orientations, suggesting generational transmission of inclusive norms as a meaningful long-term channel for D&I progress.

(vi) The Random Forest classifier achieves AUC-ROC = 0.73—adequate for discriminating active from non-active PWD hirers—with employment practices and favouritism perceptions as the dominant predictive signals.

10. IMPLICATIONS:

10.1 Theoretical Implications

This study extends the inclusion literature (Shore et al., 2011[8]; Nishii, 2013[10]) by providing empirical evidence that the structural-processual mechanisms theorised in the Purple Hiring framework operate in an emerging-market context previously under-represented in global D&I scholarship. The convergence of logistic regression and machine learning results across methods strengthens confidence in the identified predictor hierarchy and invites replication in other national and sector contexts.

10.2 Practical Implications

First, HR leaders should prioritise the formalisation of equitable employment practices—structured rubrics, blind screening, diverse panels—over awareness campaigns, given the superior predictive power of structural over attitudinal variables. Second, D&I training programmes should be redesigned as behaviourally focused, manager-accountable interventions consistent with Pendry et al. (2007)[15] and Rynes and Rosen (1995)[20]. Third, the feature importance results argue for granular assessment of age-related generational diversity norms in succession planning and recruiter training, given the relatively strong predictive role of age. Fourth, the machine learning framework presented here can be operationalised as a diagnostic organisational tool to identify HR units at risk of non-inclusive hiring behaviour and to target interventions accordingly.

11. LIMITATIONS AND FUTURE IMPLICATION

Several limitations warrant acknowledgement. First, the cross-sectional design precludes causal inference; longitudinal designs tracking hiring outcomes before and after Purple Hiring implementation are needed to establish causality. Second, the sample is restricted to IT/ITES organisations in Bengaluru, limiting generalisability to other sectors and geographies with different legal frameworks and demographic compositions. Third, the ML model accuracy of 64.4% leaves substantial unexplained variance, suggesting that additional predictors—organisational size, HR technology adoption, regulatory environment—may improve classification performance. Fourth, self-report measures of bias and discrimination perceptions are subject to social desirability bias; future research should triangulate with administrative hiring records and audit studies following Bertrand and Mullainathan (2004)[12].

Future research should: (i) conduct randomised controlled trials of Purple Hiring interventions; (ii) examine intersectional diversity dimensions simultaneously (disability × gender × caste); (iii) extend the model cross-nationally to compare its efficacy across diverse legal and cultural contexts; and (iv) explore the role of AI-assisted hiring tools—both their potential to reduce and inadvertently reproduce bias—within the Purple Hiring framework.

12. CONCLUSION

This study has provided the first empirically rigorous, machine learning-validated evaluation of Purple Hiring as a structural approach to diversity and inclusion in recruitment practices. Grounded in Social Identity Theory, Organisational Justice Theory, and Signalling Theory, and validated through convergent quantitative methods, the findings demonstrate that institutional employment practice quality—rather than individual awareness or demographic attributes—is the primary driver of inclusive hiring behaviour. The near-universal normative endorsement of equal employment (97.3%) contrasted with the substantial fraction of organisations that have not yet translated these values into active PWD recruitment (54.7%) documents the precise nature of the implementation gap that Purple Hiring is designed to bridge.

The Purple Hiring model offers organisations a coherent, evidence-based architectural alternative to the patchwork of diversity awareness campaigns and goodwill initiatives that Kalev et al. (2006)[11] identified as largely ineffective. By embedding bias-attenuation at every stage of the recruitment pipeline—from job description design through final selection—Purple Hiring transforms diversity from a dependent outcome of managerial disposition into an independent property of organisational process. In doing so, it establishes a new standard for inclusive recruitment against which the field can credibly measure progress.

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