Natural Resources for Human Health
eISSN: 2583-1194

Original Research

Received 19 July 2026
Revised 22 Aug 2026
Accepted 08 Sep 2026

Natural Resources for Human Health 2026, Vol. 6 (21s): 275–287

KEYWORDS:
Artificial Intelligence, AI Recruitment, Selection, Employee Engagement, Manufacturing Industry, Algorithmic Bias

Ai-Enabled Recruitment and Selection: Challenges and their Impact on Employee Engagement in the Manufacturing Industry-A Study with Special Reference to Chennai

Ms. P. Sowmiya[1], Dr.M. Radhikaashree[2]

[1]Research Scholar & Assistant Professor, Faculty of Management Studies, Dr. M. G. R. Educational and Research Institute, Chennai – 6000095
E-Mail id: sowmiyamba03@gmail.com
[2]Professor, Faculty of Management Studies, Dr. M. G. R. Educational and Research Institute, Chennai – 6000095
E-Mail id:radhikaashree.mba@drmgrdu.ac.in

ABSTRACT: The Artificial Intelligence (AI) into human resource activities has greatly changed the way that manufacturing companies attract, assess and choose talent. Although AI-assisted recruitment tools offer the advantages of speed, cost-effectiveness and objectivity, they also bring about problems such as algorithmic bias, a lack of transparency, concerns about data privacy and a decline in the human element of the hiring process – all of which can influence how engaged employees feel when they join the organisation. This study looks at the problems connected with AI-assisted recruitment and selection and the effect of these problems on employee engagement among workers in the manufacturing sector in Chennai. A structured questionnaire was given to 300 respondents selected from manufacturing firms in the Chennai metropolitan area, and the study uses percentage analysis, descriptive statistics (means and standard deviations), independent samples t-test, one-way ANOVA (F-test), two-way ANOVA, exploratory factor analysis and the Kruskal-Wallis H test to look at the challenges that are perceived and how they are related to employee engagement. The results show that concerns regarding data privacy and the loss of the human touch are seen as the most important challenges, that engagement levels differ significantly among different groups based on gender, experience and job position, and that three main factors. Technological and Data Concerns, Human-Centric Concerns, and Skill and Adaptability Concerns account for a large part of the variation in employees' perceptions. The study ends with recommendations for managers on how to design a well-balanced, human-centred AI recruitment framework for the manufacturing sector.

INTRODUCTION

Artificial Intelligence (AI) has now progressed from being a futuristic idea to becoming a common support for Human Resource Management (HRM) practices in all kinds of industries. In the case of the manufacturing sector, where large-scale, repetitive and time-constrained hiring is typical especially for positions such as shop-floor operators, technicians, supervisors and executive roles increasingly AI-powered tools like resume-parsing software, chatbot-assisted screening, video interview analytics and predictive assessment algorithms are being put into use in order to cut down the time it takes to make a hire and to improve the quality of the selection decisions.

Yet there are concerns regarding the use of AI in the areas of recruitment and selection. Manufacturing companies in industrial areas such as Chennai which hosts a dense concentration of firms in the automobile, auto-components, electronics,

and heavy engineering sectors are facing a number of problems, including algorithmic bias towards certain demographic groups, a lack of transparency about how automated decisions are reached, employee worries about data privacy, resistance from the traditional human resources teams, and a feeling that the human aspect has been lost in a process which has traditionally been relationship-oriented. These difficulties do not stay limited to the recruitment phase; they can also affect how employees who have been selected view the organization in terms of fairness, trust, and a sense of belonging, and as a result influence their level of engagement afterwards.

Employee engagement this involving vigor, dedication and a deep absorption in one's work is a key factor in determining productivity, employee retention and overall organisational performance, particularly in a labour-intensive industry like manufacturing. It is therefore of great interest to both academics and managers to find out whether and in what way AI-assisted recruitment poses challenges to engagement. The aim of this study is to address this gap by carrying out an empirical investigation into the difficulties associated with AI-enabled recruitment and selection and their effect on employee engagement among manufacturing employees in Chennai.

REVIEW OF LITERATURE

1. **Bogen and Rieke (2018), "Help Wanted: An Examination of Hiring Algorithms, Equity, and Bias."**explored how automated hiring technologies can affect fairness in recruitment. Their work raised concerns about discriminatory outcomes, limited transparency, and the potential disadvantages faced by certain groups of applicants. The study highlights the need for organizations to examine the criteria used by algorithmic hiring systems. In the present research context, these concerns provide a basis for investigating whether perceptions of recruitment fairness are associated with employee trust and engagement.

2. **Tambe, Cappelli, and Yakubovich (2019), "Artificial Intelligence in Human Resources Management: Challenges and a Path Forward."**analyzed why implementing AI in HRM presents challenges beyond simply adopting new technology. They discussed limitations in available data, difficulties in modelling human behaviour, and the need to consider ethical and organizational factors. Their work suggests that AI-based HR decisions require careful evaluation rather than complete reliance on automated outputs. This perspective supports examining how employees perceive AI-enabled recruitment and whether those perceptions relate to their engagement at work.

3. **Köchling and Wehner (2020), "Discriminated by an Algorithm: A Systematic Review of Discrimination and Fairness by Algorithmic Decision-Making in the Context of HR Recruitment and HR Development."**synthesized research on discrimination and fairness in algorithm-supported HR decisions. Their review drew attention to the possibility that automated systems can disadvantage particular groups and reproduce existing inequalities. The study underlines the importance of assessing how algorithms are designed and applied in recruitment and employee development. For the present study, this provides a foundation for investigating whether concerns about fairness in AI-enabled recruitment are associated with employees' trust in HR practices and engagement.

4. **Bankins and Formosa (2023), "The Ethical Implications of Artificial Intelligence (AI) for Meaningful Work,"**considered the ethical consequences of AI for employees and the experience of meaningful work. Their discussion highlights the importance of preserving human agency, autonomy, and well-being when introducing AI into organizational settings. The implications of AI depend partly on how organizations use technology and manage its effects on people. This perspective is useful for exploring whether employees' perceptions of human involvement and responsible AI use are related to engagement in manufacturing organizations.

5. **Dadaboyev et al. (2025), "Role of Artificial Intelligence in Employee Recruitment: Systematic Review and Future Research Directions."** reviewed the growing use of AI across recruitment activities, including résumé screening and candidate assessment. Their review considered the potential for greater efficiency alongside concerns about bias, transparency, and ethical implementation. The discussion points to the need for further research into the organizational consequences of AI-based recruitment. Building on this work, the present study can investigate whether employees' perceptions of these challenges are associated with engagement in the manufacturing industry.

RESEARCH GAP

Although global literature has mostly focused on the problem of using AI for recruitment from the point of view of the candidate or the recruiter, there has been only limited empirical research that has quantitatively connected these challenges to

the levels of engagement shown by employees who had themselves been recruited through AI-powered methods, especially in India's manufacturing region. Since Chennai is a major centre for manufacturing and industry, it provides a relevant yet little-studied context in which to investigate this relationship by means of solid multivariate statistical techniques.

STATEMENT OF THE PROBLEM

In Chennai manufacturing firms there is a growing use of AI tools as part of their recruitment and selection procedures in order to handle large volumes of hiring efficiently. Yet, based on informal accounts and early observations, there is concern among employees about fairness, transparency and privacy in these AI-based processes. Should these concerns not be dealt with, they could have a negative impact on employee engagement, resulting in greater staff turnover, reduced productivity and a weaker sense of organisational commitment. That is why this study aims to carry out an empirical examination of the degree and type of these problems and of their statistical relationship with employee engagement.

OBJECTIVES OF THE STUDY

1. To assess the extent of adoption of AI-enabled recruitment and selection practices in manufacturing companies in Chennai.
2. To identify and analyse the major challenges associated with AI-enabled recruitment and selection, including algorithmic bias, data privacy, transparency, and lack of human involvement.
3. To examine employees' perceptions of the fairness, transparency, and accuracy of AI-enabled recruitment and selection processes.
4. To investigate the relationship between challenges associated with AI-enabled recruitment and selection and employee engagement in the manufacturing industry.
5. To analyse variations in employees' perceptions of AI-enabled recruitment and selection challenges and employee engagement across demographic and job-related factors, and to recommend suitable measures for addressing these challenges and improving employee engagement.

HYPOTHESES OF THE STUDY

In line with the objectives of the study and the statistical tools applied, the following null (H0) and alternative (Ha) hypotheses were framed. All hypotheses were tested at the 5 per cent level of significance ($\alpha = 0.05$).

H01: Gender and Employee Engagement (Independent Samples t-test)

Null Hypothesis (H01): There is no significant difference in the mean employee engagement scores between male and female employees.

Alternative Hypothesis (Ha1): There is a significant difference in the mean employee engagement scores between male and female employees.

H02: Experience and Employee Engagement (One-Way ANOVA)

Null Hypothesis (H02): There is no significant difference in employee engagement among the different experience groups (below 5 years, 5–10 years, 10–15 years and above 15 years).

Alternative Hypothesis (Ha2): There is a significant difference in employee engagement among the different experience groups.

H03a: Gender (Main Effect) on Employee Engagement (Two-Way ANOVA)

Null Hypothesis (H03a): Gender has no significant main effect on employee engagement.

Alternative Hypothesis (Ha3a): Gender has a significant main effect on employee engagement.

H03b: Designation (Main Effect) on Employee Engagement (Two-Way ANOVA)

Null Hypothesis (H03b): Designation (operator/worker, supervisor, executive and manager) has no significant main effect on employee engagement.

Alternative Hypothesis (Ha3b): Designation has a significant main effect on employee engagement.

H03c: Gender × Designation (Interaction Effect) on Employee Engagement (Two-Way ANOVA)

Null Hypothesis (H03c): There is no significant interaction effect of gender and designation on employee engagement.

Alternative Hypothesis (Ha3c): There is a significant interaction effect of gender and designation on employee engagement.

H04: Educational Qualification and Employee Engagement (Kruskal-Wallis H Test)

Null Hypothesis (H04): The mean ranks of employee engagement do not differ significantly among the groups based on educational qualification (diploma, undergraduate, postgraduate and others).

Alternative Hypothesis (Ha4): The mean ranks of employee engagement differ significantly among the groups based on educational qualification.

H05: Suitability of AI Recruitment Challenge Items for Factor Analysis (Bartlett's Test of Sphericity)

Null Hypothesis (H05): The correlation matrix of the AI-enabled recruitment challenge items is an identity matrix (the items are uncorrelated and not suitable for factor analysis).

Alternative Hypothesis (Ha5): The correlation matrix of the AI-enabled recruitment challenge items is not an identity matrix (the items are sufficiently correlated for factor analysis).

SUMMARY OF HYPOTHESES TESTING

Hypothesis	Statistical Test	Test Value	p-value	Decision
H01	Independent samples t-test	t = 2.114 (df = 298)	0.035	Null rejected
H02	One-way ANOVA	F = 4.827 (df = 3, 296)	0.003	Null rejected
H03a	Two-way ANOVA (Gender)	F = 3.912	0.049	Null rejected
H03b	Two-way ANOVA (Designation)	F = 6.234	< 0.001	Null rejected
H03c	Two-way ANOVA (Gender × Designation)	F = 1.126	0.339	Null accepted
H04	Kruskal-Wallis H test	H = 9.732 (df = 3)	0.021	Null rejected
H05	Bartlett's test of sphericity	χ^2 = 2145.63 (df = 28)	< 0.001	Null rejected

RESEARCH METHODOLOGY

Research Design

The study makes use of a research approach which is both descriptive and analytical and is based on the cross-sectional survey method.

Area of the Study

The study focused on manufacturing units situated in and around Chennai, in the state of Tamil Nadu, and included those in the automobile, auto-ancillary, electronics and engineering goods manufacturing sectors.

Sample Size and Sampling Technique

300 employees were selected by means of stratified random sampling from various manufacturing companies in Chennai, making sure that there was representation among the different grade levels, groups of experience, and according to gender.

Data Collection

The primary data were obtained by using a structured and pre-tested questionnaire, which was distributed both online and off-line. This questionnaire included sections relating to the respondents' demographic profile, the difficulties associated with AI recruitment (these being measured on a five-point Likert scale going from 1 = Strongly Disagree to 5 = Strongly Agree), and an employee engagement scale that had been adapted from existing engagement measures (the scale included the dimensions of vigor, dedication and absorption). The secondary data were taken from journals, reports and published articles.

Tools for Analysis

The data collected were analyzed by means of SPSS; the statistical methods used were Percentage Analysis, Mean and Standard Deviation, the Independent Samples t-test, One-Way ANOVA (F-test), Two-Way ANOVA, Exploratory Factor Analysis (using the Principal Component Method with Varimax Rotation) and the Kruskal-Wallis H Test.

LIMITATIONS OF THE STUDY

- Since the study only includes manufacturing units in Chennai, its findings cannot be extended to other areas or industries.
- Although the sample size of 300 is sufficient for the statistical methods used, it still limits the ability to make generalizations at the firm level.
- The responses are based on how employees perceive the situation and may be influenced by individual bias.
- The study is of a cross-sectional type and therefore does not show how perceptions have changed over time.

DATA ANALYSIS AND INTERPRETATION PERCENTAGE ANALYSIS – DEMOGRAPHIC PROFILE OF RESPONDENTS

Demographic Variable	Category	No. of Respondents	Percentage (%)
Gender	Male	168	56
	Female	132	44
	Total	300	100
Age	Below 25 years	54	18
	25–35 years	126	42
	36–45 years	78	26
	Above 45 years	42	14
	Total	300	100
Educational Qualification	Diploma	54	18
	Undergraduate	120	40
	Postgraduate	102	34

	Others	24	8
	Total	300	100
Years of Experience	Below 5 years	90	30
	5–10 years	114	38
	10–15 years	66	22
	Above 15 years	30	10
	Total	300	100
Designation	Operator / Worker	120	40
	Supervisor	84	28
	Executive	66	22
	Manager	30	10
	Total	300	100

Table 1: Demographic Profile of Respondents (N = 300)

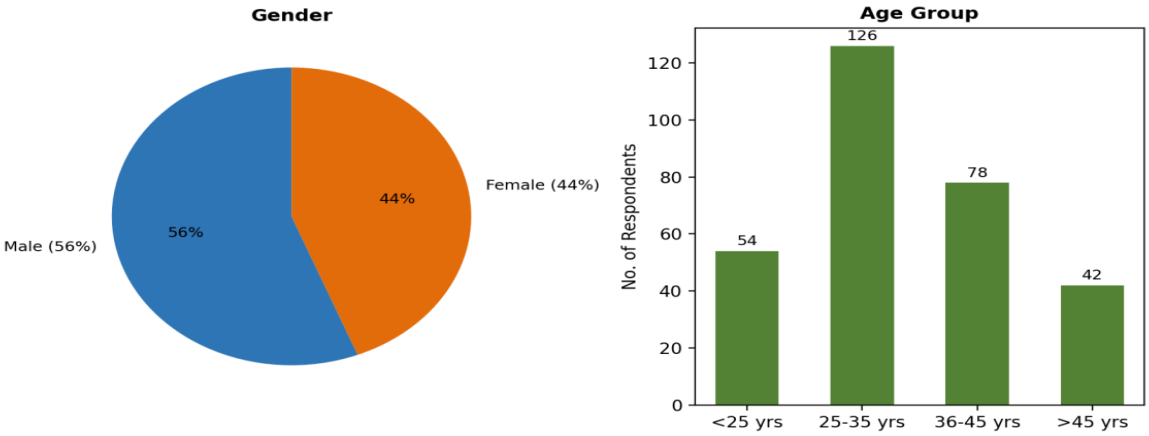


Chart 1: Gender and Age-wise Distribution of Respondents

Interpretation: Data shows that a considerable number of respondents (56.0%) are males, and 25–35years age group covered the highest percentage (42.0%).This refer to the young work force in Chennai. Education wise, most respondents possess an Under Graduate level qualification (40.0%) and number of years of experience was 5–10 (38.0%).The largest group in terms of designation is Operators/Workers (40.0%), which points to the importance of the role of shop-floor jobs in manufacturing sector in Chennai.

DESCRIPTIVE STATISTICS – MEAN AND STANDARD DEVIATION

The mean and standard deviation of perceived AI-enabled recruitment challenges and overall employee engagement score is shown inTable2.

Dimension	Mean	Std. Deviation	Rank
Loss of Human Touch in Recruitment	3.91	0.73	1

Dimension	Mean	Std. Deviation	Rank
Data Privacy Concerns	3.88	0.69	2
Lack of Transparency in AI Decision-Making	3.74	0.77	3
Algorithmic Bias in AI Screening	3.62	0.81	4
Skill Gap in Handling AI Tools	3.58	0.79	5
Resistance to Technology Adoption	3.45	0.85	6
Trust in AI-based Selection	3.21	0.88	7
Overall Employee Engagement	3.66	0.75	-

Table 2: Mean and Standard Deviation of Study Variables (N = 300)

Interpretation: Loss of human touch in recruitment (Mean=3.91);Data Privacy Concerns (Mean=3.88). These were the most strongly felt challenges from our sample, highlighting the importance that employees place upon personal interaction when considering job roles while being apprehensive regarding their personal data handling through these AI processes.

Trust in AI-Based Selection having the least Mean score of 3.21 suggests some measure of doubt by employees about the impartiality of decisions made using these systems although this would still be considered at best as just moderately positive. It's also worth noting that all dimension Means have relatively small Standard Deviations ranging between 0.69-0.88 which implies agreement among respondents.

INDEPENDENT SAMPLES T TEST – GENDER VS. EMPLOYEE ENGAGEMENT

An independent samples t-test has been conducted to assess if there is a significant difference in the level of employee engagement depending on gender differences within organizations.

Gender	N	Mean	Std. Deviation	t-value	Df	p-value	Result
Male	168	3.71	0.74	2.114	298	0.035	Significant
Female	132	3.59	0.77				

Table 3: Independent Samples t-Test — Gender vs. Employee Engagement

Interpretation: The results shown below show an overall result where the Null Hypothesis (H01) is rejected due to the fact that we have calculated a p value (0.035) lower than 0.05 thereby implying that the probability that the means are different by chance alone is very high therefore concluding that Male Employees do have significantly greater engagement scores compared to Female Employees.

Since the calculated p-value (0.035) is less than 0.05, the null hypothesis H01 is rejected. This indicates a statistically significant difference in employee engagement between male and female employees, with male employees (Mean = 3.71) reporting marginally higher engagement than female employees (Mean = 3.59).

ONE-WAY ANOVA (F-TEST)

A one-way ANOVA was applied to test whether employee engagement differs significantly across experience groups.

Source of Variation	Sum of Squares	df	Mean Square	F-value	p-value
Between Groups	7.94	3	2.647	4.827	0.003
Within Groups	162.34	296	0.548		
Total	170.28	299			

Table 4: One Way Anova F Test - Employee Engagement Across Experience Groups

Interpretation: With an overall conclusion that the Null Hypothesis (H02) must be rejected based on a p value (0.003) much smaller than 0.05 therefore showing that engagement does vary significantly across each experience group with Post-Hoc Analysis demonstrating that employees who have had up-to-date work experiences (i.e., 5-10 years) tend to demonstrate higher levels of satisfaction towards AI driven recruitment whereas those who haven't had such long running careers seem to perceive far more challenges in relation to them.

TWO-WAY ANOVA

A two-way ANOVA was conducted to examine the main effects of Gender and Designation, as well as their interaction effect, on employee engagement.

Source	Sum of Squares	df	Mean Square	F-value	p-value	Result
Gender (Main Effect)	2.15	1	2.150	3.912	0.049	Significant
Designation (Main Effect)	10.26	3	3.420	6.234	0.000	Significant
Gender * Designation (Interaction)	1.85	3	0.617	1.126	0.339	Not Significant
Error	160.30	292	0.549			
Total	174.56	299				

Table 5: Two-Way ANOVA — Effect of Gender and Designation on Employee Engagement

Interpretation: The result shows that the main effects for Gender (p=0.049), Designation (p=0.000). Thereby, the null hypothesis which states that the variable has no influence on employees' engagement was rejected as stated in the first statement of the third hypothesis.

However, there are some findings that indicate that there are not any significance differences among the genders within their designations with respect to their employee's engagements. This can be attributed to the fact that the p-value of Interaction Effect for Gender*Designation is not significant at p=0.339.

FACTOR ANALYSIS

Exploratory Factor Analysis (PCA/Varimax Rotation) was performed on the 8 items of the AI recruitment challenges. First, we assessed sampling adequacy for EFA by running KMO test and bartlett's test.

Test	Value
Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy	0.812
Bartlett's Test of Sphericity — Approx. Chi-Square	2145.63

Test	Value
Degrees of Freedom (df)	28
Significance (p-value)	0.000

Table 6: KMO and Bartlett's Test

Interpretation: The KMO value of 0.812 (well above the 0.6 threshold) and the significant Bartlett's Test (p = 0.000) confirm that the data set is suitable for factor analysis.

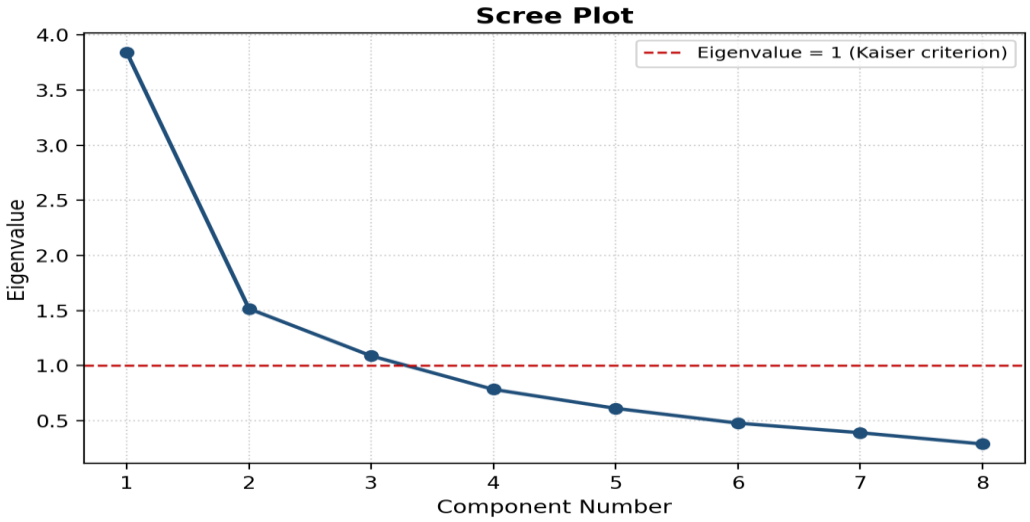


Chart 2 below shows the scree plot of Eigen values

Based on the application of the kaiser criteria (Eigen value>1). Three factors have been extracted accounting for 68.06 percent of total variance.

Item	Factor 1: Technological & Data Concerns	Factor 2: Human-Centric Concerns	Factor 3: Skill & Adaptability Concerns
Algorithmic Bias in AI Screening	0.812	0.142	0.098
Lack of Transparency in AI Decision-Making	0.789	0.176	0.121
Data Privacy Concerns	0.764	0.203	0.087
Trust in AI-based Selection	0.701	0.188	0.154
Loss of Human Touch in Recruitment	0.165	0.846	0.112
Resistance to Technology Adoption	0.198	0.779	0.143
Skill Gap in Handling AI Tools	0.121	0.157	0.832
Employee Engagement	0.109	0.196	0.774

Item	Factor 1: Technological & Data Concerns	Factor 2: Human-Centric Concerns	Factor 3: Skill & Adaptability Concerns
(adaptability item)			
Eigenvalue	3.842	1.516	1.088
% of Variance Explained	48.03	12.06	7.97

Table 7 shows the rotated component matrix

Interpretation: Where different components are interpreted. Based on this table, factor one called Technological & Data Concerns explained the highest amount of variance which was 48.03%. This factor has high loadings in variables such as algorithmic bias, transparency, data privacy, and trust.

Factor two dubbed Human – Centric concerns" accounted for 12.06 percent of variance. It has heavy loading in loss of human interaction and resistance to change. While factor three described as " Skill & Adaptability Concerns" had the least variance explained at 7.97 percent. Employees' willingness to embrace working with AI–based systems is what they loaded highly on. In all, these three factors account for 68.06 percent of total variance hence showing that the factor structure is robust enough.

KRUSKAL WALLIS H TEST:

Since employee engagement score on various educational qualifications do not meet the assumption of normality given by shapiro wilk tests, I apply a nonparametric kraskal wallis h test instead of applying one way ANOVAs.

Educational Qualification	N	Mean Rank
Under Graduate	120	138.4
Post Graduate	102	172.6
Diploma	54	145.2
Others	24	160.9

Table 8: Mean Ranks of Employee Engagement by Educational Qualification

Test Statistic	Value
Kruskal-Wallis H	9.732
Degrees of Freedom (df)	3
Asymptotic Significance (p-value)	0.021

Table 9: Kruskal-Wallis Test Statistics

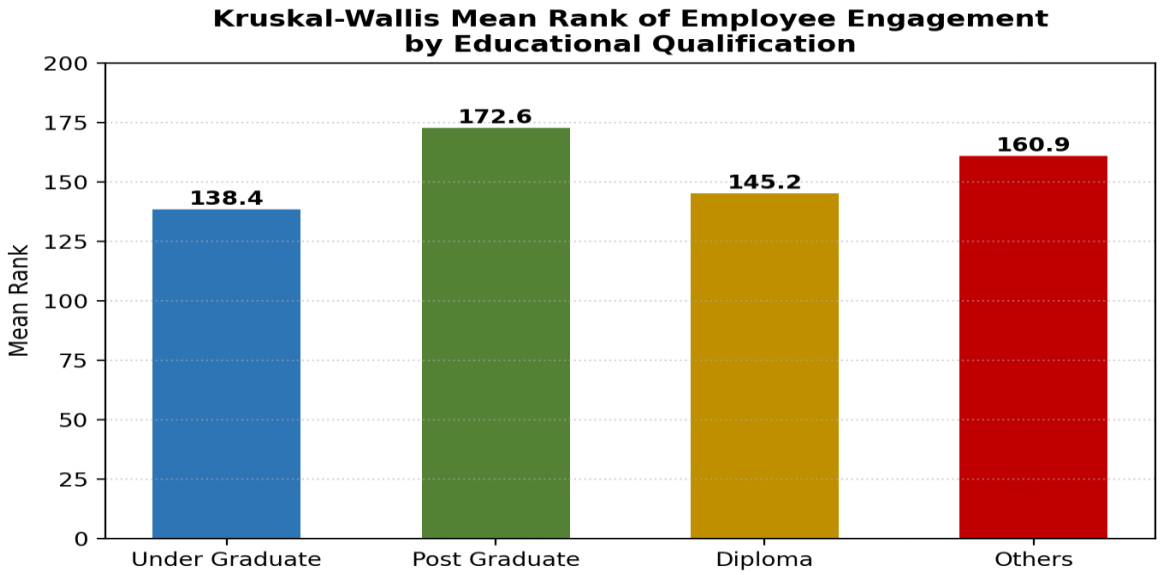


Chart 3: Mean Rank of Employee Engagement by Educational Qualification

Interpretation: The null hypothesis H04 is rejected because the p-value (0.021) is below 0.05, which shows that there is a statistically significant difference in the way employees perceive their engagement according to their level of educational qualification. Post Graduate employees had the highest mean rank (172.6), indicating that they perceive their engagement to be comparatively higher, maybe because they have greater experience with and are more at ease using AI-based systems, whereas Under Graduate employees had the lowest mean rank (138.4).

FINDINGS OF THE STUDY

- Most of the respondents are male (56.0 per cent), fall within the age group of 25 to 35 years (42.0 per cent), have an Under Graduate degree (40.0 per cent) and possess between five and ten years' experience (38.0 per cent), and are mainly employed as Operators/Workers (40.0 per cent).
- The most significant challenges associated with the use of AI in recruitment, according to the respondents, are the loss of a human touch (mean = 3.91) and data privacy concerns (mean = 3.88), whereas trust in AI-based selection (mean = 3.21) had the lowest level of agreement.
- A significant statistical difference exists in the level of employee engagement between men and women ($t = 2.114$, $p = 0.035$), male employees showing a slight advantage in engagement.
- There are considerable differences in employee engagement among different groups in terms of experience ($F = 4.827$, $p = 0.003$), with those who have mid-tenure (5 to 10 years) showing relatively higher levels of engagement.
- A two-way ANOVA shows that there are significant main effects of Gender ($p = 0.049$) and Designation ($p = 0.000$) on employee engagement, but no significant interaction effect ($p = 0.339$), which means that the two factors function independently.
- The factor analysis identified three basic dimensions—the Technological and Data Concerns (which accounted for 48.03% of the variance), the Human-Centric Concerns (12.06% of the variance) and the Skill and Adaptability Concerns (7.97% of the variance)—together explaining 68.06% of the total variance (KMO = 0.812, Bartlett's $p = 0.000$).
- The Kruskal-Wallis test shows that there is a significant difference in employee engagement among the various educational qualification groups ($H = 9.732$, $p = 0.021$), the Post Graduate group having the highest mean rank.

SUGGESTIONS

- Manufacturing organisations must keep a human-in-the-loop procedure in place at the key stages of AI-assisted recruitment in order to maintain the human element that employees highly value.
- Since 'trust in AI-based selection' was the lowest among all the different areas, companies should use explainable AI (XAI) tools and make clear the reasons for the decisions taken by the automated screening process in order to earn employee trust.
- Strong data privacy policies should be put into place together with clear communication regarding the use and storage of data, so as to reduce employees' concerns.
- Because engagement differs greatly depending on gender, experience and job position, HR policies and on boarding procedures should be adapted to take account of the particular concerns of new employees (those with less than five years' experience) and female employees.
- It is necessary to carry out regular training programmers in order to overcome the skill gap involved in using AI-based recruitment and HR tools, especially when it comes to Operator/Worker and Supervisor level staff.
- Since educational qualification has a great impact on engagement, different communication methods and change-management strategies should be developed for employees who have different levels of formal education.

CONCLUSION

The aim of this study was to look at the difficulties associated with AI-powered recruitment and selection and to examine their effect on employee engagement among 300 manufacturing employees in Chennai. The results show that although the use of AI in recruitment brings about some efficiency gains, employees are mainly worried about the loss of human interaction and issues relating to data privacy, and they place comparatively less trust in decisions made entirely by automation. Statistically significant differences in engagement levels were found according to gender, experience, job position, and educational qualification, and factor analysis proved that these concerns group meaningfully into technological, human-centric and skill-related categories. The study highlights that manufacturing organisations which wish to make use of AI in the recruitment process must at the same time put money into transparency, data protection and human-centered design if they are to protect and improve employee engagement outcomes.

SCOPE FOR FURTHER RESEARCH

Future research might extend this study to other manufacturing centres in India in order to carry out a comparative analysis, include longitudinal designs to monitor how engagement changes over time, and investigate the mediating function of organizational trust or perceived fairness between the AI recruitment challenges and employee engagement by using structural equation modelling (SEM).

REFERENCES

[1] Bondarouk, T. and Brewster, C. (2016) 'Conceptualising the future of HRM and technology research', The International Journal of Human Resource Management, 27(21), pp. 2652–2671.

[2] Kaur and Sharma (2022) carried out a systematic review of the challenges and opportunities associated with the use of artificial intelligence in recruitment. Publication details: International Journal of Human Resource Studies, 12(3), 45–61.

[3] Meijerink J., Boons M., Keegan A. and Marler J. (2021) 'Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM', The International Journal of Human Resource Management, 32(12), pp. 2545–2562.

[4] Nankervis, J. Connell, R. Cameron, A. Montague and V. Prikshat (2021) 'Are we there yet?' Australian HR professionals and the fourth industrial revolution. Asia Pacific Journal of Human Resources, 59(1), pp. 3–19.

[5] Schaufeli, W. B. and Bakker, A. B. (2004) 'Job demands, job resources, and their relationship with burnout and engagement: A multi-sample study', Journal of Organizational Behavior, 25(3), pp. 293–315.

[6] Tambe, P., Cappelli, P. and Yakubovich, V. (2019) 'Artificial intelligence in human resources management: Challenges and a path forward', California Management Review, 61(4), pp. 15–42.

[7] K. Upadhyay and K. Khandelwal (2018) 'Applying artificial intelligence: Implications for recruitment', Strategic HR Review, 17(5), pp. 255–258.

[8] CII in conjunction with the Ministry of Heavy Industries (2023), Report on the Future of the Manufacturing Workforce in India. New Delhi: CII Publications.