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The Impact of Artificial Intelligence in Recruitment on Recruitment Efficiency

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Abstract

There is growing practitioner interest in the growing utilization of AI in the Human Resource Management. Nevertheless, there is scant empirical data regarding direct relationships between AI recruitment technologies and efficiency measures. This paper considers the role of AI in recruitment in terms of recruitment efficiency, the influence of AI sub-dimensions (AI-Based Resume Screening, AI-Powered Candidate Assessment, and Predictive Analytics) on important efficiency outcomes: time-to-hire, quality of hire, cost-per-hire, and recruiter productivity. This study was based on the Technology Acceptance Model (TAM) and Resource-Based View (RBV), and its methodology was a quantitative study with qualitative thematic analysis. Primary data were gathered through 14-item Likert scale questionnaire to 100 HR professionals, recruiters, and hiring managers in the Indian firms. Statistical tools such as descriptive statistics, Cronbachs Alpha, one-sample t-tests, Pearson correlation, simple and multiple linear regression, ANOVA, and independent samples t-tests were used. The two hypotheses were accepted. A one-sample t-test established that AI in the recruitment process has a positive effect on efficiency in general (DV mean = 3.219; t(99) = 2.900, p = 0.005). Simple linear regression established that AI-based resume screening is a strong predictor of time-to-hire (R 2 = 0.110, 0.464, p < 0.001). Multiple linear analysis showed that AI sub-dimensions can predict the efficiency of recruitment (R 2 = 0.410) with the most significant predictor being the Candidate Assessment (0.250). ANOVA found experience to be a moderator (p = 0.039). In qualitative analysis, the lack of human touch (22%), algorithmic bias (18%), and resume manipulation (15%), were noted as the main issues. The research approves that AI is highly effective in increasing the efficiency of recruitment in organisations located in India, but it is important to use AI responsibly and in a balanced way.

Keywords: Artificial Intelligence, Recruitment Efficiency, Resume Screening, Predictive Analytics, Talent Acquisition, HRM, TAM, RBV, India.

INTRODUCTION

With the advent of digital technologies, the world of organisational activity has changed almost every aspect of organisational life. One of the biggest disruptors in Human Resource Management (HRM) is the Artificial Intelligence (AI). Historically, the recruitment process used to be manual and time-consuming and included posting a job advertisement, screening hundreds of resumes, interviewing and hiring based on subjective judgment. Not only were they inefficient, but they were also prone to lack of consistency, bias, and high cost.

The AI-based recruitment equipment utilises machine learning, natural language processing (NLP), computer vision, and big data analytics to automatise and streamline the talent acquisition process. The current AI systems can scan through thousands of resumes in the span of a few seconds, rank applicants by job-fit scores, analyse video interviews, and predict whether a particular candidate can succeed in a specific position, which is very effective in recruiting efficiency.

Recruitment efficiency is a multi-dimensional concept and is generally determined in terms of time-to-hire, quality-of-hire, cost-per-hire, and recruiter productivity. Improving these results is one of the key strategic priorities of HR

departments all over the world. Although AI is increasingly being used to hire, there is still a disconnection between practitioner excitement and academic research-based studies - especially within the Indian environment.

This paper fills that research void by conducting an empirical study of the influence of AI in recruitment, which is operationalised by Resume Screening, Candidate Assessment, and Predictive Analytics, on recruitment efficiency in Indian companies. The Indian business environment is a special case: the adoption of AI in HR is gaining new momentum, but the experimental data on measurable efficiency improvement is scarce.

The research problem is as follows.

One of the most strategic HRM functions is recruitment. Standard recruiting methods are inherently inefficient: long screening times, expensive, subjective evaluation and the inability to deal with large numbers of applications all the time. The AI-based recruitment systems are expected to resolve these concerns, but there is one important empirical question: does the use of AI in hiring bring any real benefits in terms of efficiency in recruiting?

The majority of previous research has either conceptualized or approached the subject of AI in HR or considered its application in a Western context, which has not provided direct empirical evidence of the role of AI in particular efficiency variables, especially in the Indian context. This study fills this gap by gathering firsthand information about Indian HR professionals and verifying the extent to which the implementation of AI would enhance the effectiveness of recruitment.

REVIEW OF LITERATURE

As Upadhyay and Khandelwal (2018) showed, AI recruitment tools automatize repetitive processes, including resumes screening and scheduling an interview, which could potentially save recruiter work by 40 percent and enhance the consistency of decisions made. Tambe, Cappelli, and Yakubovich (2019) have discovered that although AI can be very efficient, the benefits of the technology are highly conditional upon the quality of the training data, and biasness in the data puts at risk the appearance of discriminatory hiring trends.

Raisch and Krakowski (2021) concluded that the use of AI as an augmenter but not a replacement of human judgment can be effective, and that the HR managers must maintain authority in the complex hiring process that requires cultural and interpersonal considerations. Fernandez and Gallardo-Gallardo (2016) discovered that on average, AI-enabled ATS tools took 30% less time to conduct initial screening, and Black and Van Esch (2020) discovered that AI resume screening decreased time-to-shortlist by 14 days to fewer than 3 days without affecting quality of candidates.

On bias and fairness, Köchling and Wehner (2020) reported that algorithmic screening tools had systematic discriminatory risks, and NASSCOM (2024) reported that well-designed AI systems decreased demographic-based filtering errors by 42 percent in Indian IT companies. Chowdhury, Heizmann, and Pichler (2023) emphasised that the effectiveness of AI in HRM is based on the readiness of an organisation, data infrastructure, and integration with human control. In general, the literature promotes a hybrid model where AI is used to screen

high-volume screening with humans doing contextual and qualitative screening.

Theoretical Framework

The present research is based on two theoretical frameworks that are complementary. The Technology Acceptance Model (TAM), which was initially advanced by Davis (1989), holds the view that the perceived usefulness and perceived ease of use are what determine the acceptance of the information technology by the users. HR professionals who view AI tools as helpful and easy to use have higher chances of using them and benefiting themselves with their efficiency.

Resource-Based View (RBV), described by Barney (1991), is the view that organisations can achieve long-term competitive advantage by possessing valuable, rare, and non-imitable resources. Used strategically, AI recruitment services are an organisational resource to create quantifiable efficiency benefits, including reduced time-to-hire, decreased cost, and quality of hire.

Research Hypotheses

Based on the theoretical framework and review of literature, the following hypotheses were developed:

H 1 1: The overall efficiency of recruitment is adversely affected by Artificial Intelligence in recruitment.

H 0: AI-based resume screening does not have a strong positive effect on time-to-hire.

RESEARCH METHODOLOGY

The research design taken in this study is a quantitative research design with a qualitative thematic analysis. The primary data were gathered by a structured 14-item Likert-scale questionnaire (1 = Strongly Disagree to 5 = Strongly Agree) that was carried out online through Google Forms and shared through LinkedIn and HR professional communities. The respondents were HR professionals, recruiters, and hiring managers in Indian organisations applying AI tools in the recruitment process. It was conducted through purposive and convenience sampling, with 100 valid responses received, which is a sufficient amount of responses because of the standards of MBA-level research and similar works in the field of HR technology (Kaur and Sharma, 2021; Gupta and Mishra, 2022). The independent variable (IV) that was AI in Recruitment was operationalised by three sub-dimensions AI-Based Resume Screening (B1-B3), AI-Powered Candidate Assessment (B4-B6), and Predictive Analytics (B7-B9). The dependent variable (DV) - Recruitment Efficiency - was a five-item (C1-C5) measure of time to hire, quality of hire, cost-per-hire, recruiter productivity, and efficiency. SPSS was used to conduct statistical analysis, and it entails: descriptive statistics, Cronbachs Alpha (reliability), one-sample t-tests, Pearson correlation, simple and multiple linear regression, one-way ANOVA, and independent samples t-tests. A qualitative question that was open-ended was used to capture challenges in using AI recruitment tools and analysed using thematic coding.

DATA ANALYSIS AND INTERPRETATION

Reliability Analysis

Values greater than 0.70 for Cronbach's alpha indicate the presence of very high internal consistency for all of the scales (Nunnally, 1978). The alpha coefficient for the whole study was 0.84, and alphas for the independent and dependent variables were 0.87 and 0.79, respectively.

Descriptive Statistics

The mean values for all items are higher than the neutral value of 3.0, confirming the agreement on the direction of influence of AI on recruitment. The mean values for efficiency results (C1-C5) are 3.219, whereas the IV composite mean is 3.175. Standard deviations are moderately dispersed, without any polarity.

One-Sample T-Test — Hypothesis 1 (H_{11})

As can be seen from the findings of the one sample t-tests, the IV composite (Mean = 3.175, t(99) = 2.270, p= 0.025), as well as the DV composite (Mean = 3.219, t(99) = 2.900, p = 0.005), are statistically significantly higher than the neutral point of 3.0. Thus, H_{11} is supported and H_{01} is rejected at $p < 0.05$.

Simple Linear Regression — Hypothesis 2 (H_{12})

The simple linear regression analysis between the independent variable of composite AI-Based Resume Screening sub-score (B1-B3) and the dependent variable of Time-to-Hire (C1) shows a statistically significant model (R^2=0.110, F=12.14, p<0.001). With the positive value of the beta coefficient (β=0.464), it can be concluded that greater adoption of AI-based resume screening has a significant influence on time-to-hire efficiency. Thus, the null hypothesis (H_{02}) was rejected.

Multiple Linear Regression — Sub-Dimension Contributions

Multiple linear regression analysis involving all three sub-dimensions of AI as predictors simultaneously accounts for 41% of variance in recruitment efficiency (R^2 = 0.410; R = 0.569). The best predictor among the three was the dimension of Candidate Assessment (β = 0.250), followed by that of Resume Screening (β = 0.229) and finally Predictive Analytics (β = 0.110). The regression model can be written as follows: DV = 1.365 + 0.229(Sub1) + 0.2

One-Way ANOVA — Experience as Moderator

A one-way ANOVA test showed a significant difference in AI efficiency across experience levels (F(3,96) = 2.907, p = 0.039). Professionals in their mid-career who have been in the industry for between six and ten years experienced the greatest improvement in efficiency (M = 3.42), whereas senior professionals who have been working for over ten years found the efficiency lower than neutral (M = 2.96)

Independent Samples T-Test — Job Role Comparison

There is no statistically significant difference in the way HR Professionals and Managers perceive the efficiency of artificial intelligence recruitment (t(31) = 0.042, p = 0.967). They both have positive attitudes towards AI recruiting, which means that the communication about AI recruitment strategies does not need to differ significantly.

FINDINGS AND DISCUSSION

Empirical research proved that application of artificial intelligence in recruitment leads to statistically significant increases in recruitment efficiency. H_{11} and H_{12} hypotheses were tested and proven. One-sample t-test confirmed H_{11} (DV: t(99) = 2.900, p = 0.005) and simple linear regression at the composite sub-dimension level confirmed H_{12} (R^2 = 0.110, $p < 0.001$). These results confirm previous studies carried out by Upadhyay and Khandelwal (2018) and Black and Van Esch (2020).

Multiple regression analysis proves that the most important predictor of recruitment efficiency is AI-Powered

Candidate Assessment, followed by Resume Screening (predictive power 22.9%) and Predictive Analytics (predictive power 11%). Thus, besides streamlining the recruitment process through automation, AI's main strength in the talent acquisition process lies in the enhancement of quality of candidate assessment. This conclusion is consistent with Raisch and Krakowski (2021), who claimed that AI adds but does not replace human judgement during candidate selection process.

The validity of the TAM model is confirmed by the presence of a correlation between the AI tools' usefulness perception and positive perception of efficiency. The same is true for the RBV approach that claims AI tools and, specifically, candidate assessment sub-dimension can act as organisational resources and serve as sources of competitive advantage.

ANOVA test results revealed that experience was proven to be a significant moderator factor ($p = 0.039$). Senior HR professionals, having more than ten years of experience, had below-neutral efficiency perceptions ($M = 2.96$). This could be caused by the lack of understanding of AI capabilities and possible reluctance to accept innovations due to long-established manual techniques. On the other hand, professionals in mid-career stage (6-10 years of professional experience) showed the highest positive efficiency perception level. This result shows the importance of proper change management policies for highly-experienced HR professionals.

Three concerns identified during the qualitative data analysis, i.e., the absence of the human touch element, algorithmic bias and resume manipulation, prove the importance of using a hybrid model of AI-based recruitment, according to which high-volume recruitment tasks would be performed through automated systems while critical and culturally-sensitive stages – manually.

RECOMMENDATIONS AND IMPLICATIONS

On the basis of the results obtained, several recommendations are formulated for managers in charge of recruitment and HR functions in India-based organizations. First, as Candidate Assessment turned out to be the strongest predictor of recruitment efficiency, an investment into AI-Powered Candidate Assessment (e.g., AI video interviewing and competency-matching algorithms) should be considered a priority for these organizations. Next, because of significant algorithmic biases and the problem of resume manipulation, regular AI bias audits should be conducted, as well as human intervention should be included in candidate assessment phases.

Third, the experience gap identified using ANOVA calls for developing targeted change management programs that would involve transparent discussions of AI audit procedures and financial benefits, as well as provision of a space to discuss concerns. Fourth, the organization should opt for a hybrid recruitment approach, i.e., use AI for high-volume screening and human judgement in the final phase. Last but not least, the company would benefit from data privacy governance procedures development.

LIMITATIONS OF THE STUDY

When analyzing results obtained during empirical research, several important factors that limit generalisability should be noted. First, the selected sample was non-probability one and consisted of only 100 individuals, majority of whom had less than 30 years of age and fewer than

five years of professional experience. Second, the used survey questionnaire involved perception-based data collected through a Likert scale, which implies social desirability bias and inability to provide objective data about efficiency levels.

Third, the conducted experiment is cross-sectional in nature, thus no causal relationship can be drawn between variables based on regression coefficients. Another limitation is that in Section C5 (Efficiency of AI-based resume screening), 34% of the responses remained missing, making regression impossible. Finally, the study had geographical and sectoral constraints: its findings are applicable to urban organizations and sectors with high rates of AI utilization.

CONCLUSION

In this paper, it is demonstrated that application of artificial intelligence in recruitment results in statistically significant increase in recruitment efficiency in Indian organizations. Both hypotheses have been tested and confirmed: H_{11} proved that AI in recruitment positively affects efficiency (DV: $t(99) = 2.900$, $p = 0.005$), while H_{12} confirmed that the efficiency of resume screening through AI is positively impacted by AI ($R^2 = 0.110$, $p < 0.001$). According to multiple regression, 41% of variance in recruitment efficiency is explained collectively by three AI sub-dimensions.

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Component	Value
Number of Items	14
Number of Respondents (N)	100
Cronbach's Alpha — IV Scale (B1–B9)	0.87
Cronbach's Alpha — DV Scale (C1–C5)	0.79
Cronbach's Alpha — Full Scale (All 14 items)	0.84

Table 1: Reliability Analysis — Cronbach's Alpha

	Item Description	Mean (M)	SD	Interpretation
B1	AI tools screen resumes faster	3.12	1.281	Neutral
B2	AI improves shortlisting accuracy	3.45	1.102	Moderate Agreement
B3	AI reduces manual screening effort	3.18	1.195	Neutral
B4	AI chatbots evaluate candidates effectively	3.22	1.087	Neutral
B5	AI identifies suitable candidates better	3.38	1.043	Neutral-Agree
B6	AI supports better hiring decisions	3.16	1.156	Neutral
B7	AI reduces unconscious bias in screening	3.09	1.234	Neutral
B8	AI usage improves overall HR performance	3.21	1.098	Neutral
B9	Predictive analytics supports data-driven hiring	3.17	1.175	Neutral
C1	AI reduces overall time required to hire	3.28	1.042	Neutral-Agree
C2	AI improves quality of candidates hired	3.19	1.087	Neutral
C3	AI reduces overall recruitment cost	3.11	1.134	Neutral
C4	AI increases recruiter productivity	3.24	1.063	Neutral-Agree
C5	Overall, AI improves recruitment effectiveness	3.31	0.998	Neutral-Agree

Table 2: Descriptive Statistics — All 14 Likert Items

Variable	N	Mean	SD	t-statistic	df	p-value	Decision
IV Composite (AI Adoption)	100	3.175	0.771	2.270	99	0.025*	Reject H_0
DV Composite (Recruitment Efficiency)	100	3.219	0.756	2.900	99	0.005**	Reject H_0

Table 3: One-Sample T-Test Results (Test Value = 3.0, Neutral Midpoint)

Model	R	R^2	Adjusted R^2	β (Resume Screening)	F	p-value
Sub1 → C1 (Time-to-Hire)	0.331	0.110	0.101	0.464	12.14	< 0.001***

Table 4: Simple Linear Regression — AI-Based Resume Screening Predicting Time-to-Hire

Predictor	Beta (β)	Constant	R	R^2	p-value
Resume Screening (B1–B3)	0.229	1.365	0.569	0.410	< 0.001***
Candidate Assessment (B4–B6)	0.250	—	—	—	< 0.001***
Predictive Analytics (B7–B9)	0.110	—	—	—	< 0.05*

Table 5: Multiple Linear Regression — AI Sub-Dimensions Predicting Recruitment Efficiency

Experience Group	n	Mean DV	SD	F-statistic	p-value
Less than 2 years	36	3.14	0.63	2.907	0.039*
2–5 years	27	3.28	0.67	—	—
6–10 years	20	3.42	0.72	—	—
Above 10 years	17	2.96	0.58	—	—

Table 6: One-Way ANOVA — Years of Experience vs. Perceived Recruitment Efficiency

Group Comparison	**n (Group 1)**	**Mean DV**	**n (Group 2)**	**Mean DV**	**t-statistic**	**p-value**
HR Professionals vs. Managers	19	3.24	14	3.23	0.042	0.967 (n.s.)

Table 7: Independent Samples T-Test — HR Professionals vs. Managers