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A COMPARATIVE STUDY OF EFFECTIVE HIRING PROCESSES IN INDIA: THE IMPACT OF AI AND DATA ANALYTICS

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Abstract *In response to India's evolving labour market and policy reforms like the National Education Policy (NEP) 2020, organisations are increasingly adopting Artificial Intelligence (AI) and data analytics to streamline recruitment processes (MoE, 2020)[1]. However, the extent and effectiveness of AI integration across sectors remain largely underexplored, especially in relation to the skill-employability gap highlighted in government and NITI Aayog reports (NITI Aayog, 2021). This study conducts a comparative analysis of hiring practices in IT, non-IT, and public sector organisations using secondary data, policy documents, and organisational case studies. Drawing on frameworks from emerging HRM literature (Meijerink et al., 2021; Chamorro- Premuzic et al., 2019), the study evaluates adoption maturity, recruitment outcomes, and ethical considerations. Findings show that while IT firms leverage AI tools for end-to-end hiring, public and non-IT sectors face systemic barriers related to digital infrastructure, resistance to change, and policy alignment. The paper concludes by proposing a sector-specific framework for responsible and scalable AI adoption in hiring, with implications for education-to-employment linkages and workforce development strategy.*

Keywords: *AI in Recruitment, NEP 2020, Predictive Hiring, Public Sector HRM, Skill Gap, India*

INTRODUCTION

The adoption of Artificial Intelligence (AI) in recruitment is grounded in broader theories of technological acceptance, innovation diffusion, and HR-technology alignment. One of the most widely used frameworks to explain technology uptake in organisational settings is the Technology Acceptance Model (TAM) developed by Davis (1989). TAM posits that two key perceptions, usefulness and ease of use, significantly influence an individual's intention to adopt a technology. These constructs remain central to understanding how HR professionals perceive and embrace AI-based hiring tools in practice (Venkatesh & Davis, 2000).

Complementing TAM, the Diffusion of Innovations Theory[2], by Rogers (2003) offers a macro- sociological lens by categorising organisations into five adopter types: innovators, early adopters, early majority, late majority, and laggards. This framework becomes particularly useful when comparing AI hiring trends across different sectors. For instance, IT companies in India are often classified as innovators or early adopters, having swiftly incorporated AI-powered platforms such as HireVue, SHL[3], and Pymetrics.

In contrast, public sector organisations, especially state-run institutions tend to occupy the laggard end of the spectrum, constrained by bureaucratic rigidity, funding limitations,

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[1] The National Education Policy (2020) emphasises digital literacy and employability skill development across education levels, aiming to bridge the academia-industry gap and support workforce readiness.

[2] *Diffusion of Innovations Theory* is widely used in tech adoption studies to segment users based on openness to change—crucial in HR tech uptake analysis.

[3] HireVue and SHL use video-based and game-based assessments powered by AI to evaluate cognitive ability, personality fit, and communication style. These are widely adopted in Indian IT firms during campus recruitment.

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and procedural adherence (Choudhury & Patnaik, 2022). From a behavioural science[4] perspective, Predictive Validity Theory, a sub-discipline of psychometric theory provides justification for the use of algorithmic tools in recruitment. This theory supports the idea that algorithm-derived assessments, such as cognitive ability tests or skill evaluations, can statistically forecast job performance (Schmidt & Hunter, 1998). Consequently, predictive analytics has been gaining traction as a valid method for shortlisting candidates in high-volume hiring environments.

Furthermore, recent scholarship in HRM underscores the emergence of augmented intelligence[5], a paradigm where AI serves as a complement rather than a replacement for human judgment (Chamorro-Premuzic et al., 2019). This "human-in-the-loop" approach supports ethical and contextual hiring, particularly in decision-heavy industries where cultural fit and interpersonal dynamics are difficult to quantify. In the Indian context, policy reforms like the National Education Policy (NEP 2020) have prioritised employability and digital skill development, aiming to align academic outputs with industry hiring requirements (MoE, 2020). Despite this, systemic implementation gaps remain. Reports by NITI Aayog (2021) reveal that many government institutions still operate using outdated recruitment protocols, lacking both digital infrastructure and change management strategies.

On the other hand, IT sector firms are at the forefront of AI-driven hiring innovation. These organisations deploy end-to-end AI tools for resume screening, behavioural simulations, gamified[6] cognitive testing, and even video-interview scoring. Non-IT sectors such as banking, FMCG, and consulting occupy a transitional space, adopting AI selectively, often for high-volume roles or skill-specific assessments, while maintaining human oversight in the final selection stages (Joshi & Tripathi, 2021). In summary, the landscape of AI-powered hiring in India is diverse and stratified, shaped by organisational maturity, sector-specific constraints, and the regulatory ecosystem. Understanding this theoretical foundation is essential for designing equitable, scalable, and efficient recruitment strategies.

METHODOLOGY

This study adopts a qualitative, comparative approach grounded in secondary data analysis to explore the integration of AI in recruitment processes across three major sectors in India: IT, non-IT, and public sector organisations. The objective is to analyse how organisations leverage AI technologies for talent acquisition and the challenges they face in doing so. Drawing on prior frameworks in digital HRM and innovation diffusion, this research investigates sector-specific trends and assesses the impact of AI on hiring quality, efficiency, and inclusivity.

Following Yin's (2014) case study methodology and Miles and Huberman's (1994) principles for qualitative data analysis, this paper uses publicly available reports, white papers, academic studies, and case documentation from leading Indian firms and policy think tanks. Narratives and data points were triangulated to ensure reliability and thematic consistency across cases. The analysis also applies elements of documentary research[7], focusing on organisational practices highlighted in AI hiring reports from NASSCOM (2023), Deloitte (2021), KPMG (2020), and NITI Aayog (2021). To further enrich insights, interviews and commentary from HR leaders (published in trade journals and webinar transcripts) were included for contextual understanding.

RESEARCH DESIGN

This is an exploratory, descriptive study that employs multi-case comparative analysis. The unit of analysis is the organisation's recruitment process, and the sampling technique is purposive[8], selecting cases where AI integration in hiring is documented, evolving, or experimental.

Sampling Strategy

This study focuses on a purposive sample of nine organisations across three key sectors in India IT, non-IT, and public sector enterprises to explore the adoption and application of AI in recruitment processes. Each sector was represented by three firms, selected based on the availability of verifiable documentation and prominence in industry case studies. The IT sector includes Infosys, TCS, and Wipro, all of which are recognised leaders in digital HR transformation. The non-IT sector comprises ICICI Bank, Hindustan Unilever, and Larsen & Toubro, each known for incorporating emerging technologies in talent acquisition. Public sector entities such as ONGC, SBI, and

[4] *Behavioural Assessments* in recruitment evaluate personality traits, risk tolerance, and decision-making style beyond just technical skills.

[5] *Augmented Intelligence* emphasises AI as a supportive tool rather than a replacement for human decisions, enabling ethical and nuanced hiring.

[6] Gamified cognitive tests often measure attention span, decision-making under stress, and risk tolerance. Pymetrics and similar platforms are used to create engaging candidate experiences while generating behavioural data.

[7] *Documentary Research* involves analysing publicly available materials such as policy briefs, reports, and white papers to uncover patterns in organisational practices.

[8] *Purposive Sampling* ensures cases are selected not randomly but based on relevance to the research objective—particularly useful in qualitative comparative studies like this.

NTPC are included to examine digital hiring evolution in government-controlled environments. These organisations were identified through references in benchmarking reports, media articles, and case mentions in industry white papers related to AI implementation in HR.

Data Collection Sources

Data were drawn from a combination of secondary and documentary sources, ensuring diversity and depth of insight. Primary materials included industry and policy reports published by bodies such as NASSCOM (2023), Deloitte (2021), KPMG (2020), and NITI Aayog (2021), as well as strategic reforms outlined in the National Education Policy (2020). Additionally, publicly available white papers, company websites, and recruitment portal documentation were reviewed to map AI-related hiring practices. To contextualise practices within organisational culture, insights from media interviews, panel discussions, and webinars featuring CHROs and talent acquisition leaders were incorporated. These qualitative insights added narrative depth to the analysis and supported sector-specific interpretations. The research also referenced peer-reviewed academic literature on AI in human resource management, particularly concerning ethical and predictive dimensions of recruitment.

Data Analysis Procedure

The data were analysed using thematic coding techniques[9], consistent with Miles and Huberman's (1994) approach to qualitative content analysis. Key insights were extracted through iterative reading and coding, enabling the identification of common and contrasting themes across sectors. Five thematic categories emerged as core to the analysis:

- The maturity level of AI adoption in recruitment processes.
- The types of tools and their applications, including resume parsers[10], chatbots, and gamified assessments,
- Efficiency outcomes, particularly reductions in time-to-hire and cost, as well as improvements in candidate experience,
- Ethical and implementation challenges, such as transparency, bias, and explainability, and
- Organisational readiness for future AI integration, linked to leadership vision and alignment with national digital strategies.

A comparative matrix was developed to analyse patterns both within and across sectors. This matrix facilitated the identification of sectoral divergences and convergences, while triangulated data from multiple sources enhanced validity and interpretive reliability.

Data Analysis

To investigate sector-specific AI adoption in recruitment, thematic content analysis was applied to documents, industry reports, and organisational case studies collected across IT, non-IT, and public sector firms. This analytical approach followed Miles and Huberman's (1994) iterative coding technique, identifying recurring markers across recruitment workflows, technological infrastructure, and HR decision points. Patterns were then aligned with conceptual themes based on prior frameworks in predictive analytics (Schmidt & Hunter, 1998), TAM[11] (Davis, 1989), and augmented intelligence theory (Chamorro-Premuzic et al., 2019).

The collected data were organised into three overarching analytical categories: the maturity and integration level of AI in recruitment, the perceived impact of AI tools on hiring outcomes, and the key barriers and enablers influencing adoption. These categories were derived inductively during thematic coding and served as the basis for comparative interpretation across sectors. In terms of AI maturity and integration, the analysis revealed a significant variance between the IT, non-IT, and public sectors. IT firms demonstrated the highest degree of AI adoption, with end-to-end automation embedded in early-stage recruitment processes such as resume parsing, chatbot-driven[12] candidate engagement, and online assessments. These firms have integrated AI tools seamlessly with their broader human resource management systems. In contrast, non-IT firms exhibited a more cautious and selective use of AI, typically deploying these tools in high-volume, entry-level hiring scenarios while continuing to rely on human judgment for critical hiring decisions. Public sector organisations, however, showed minimal AI integration.

[9] *Thematic Coding* allows researchers to group qualitative data into meaningful categories, revealing cross-sector patterns in adoption and challenges.

[10] *Resume Parsers* are AI-powered tools that extract key candidate data (e.g., skills, experience) to streamline shortlisting from large applicant pools.

[11] *TAM (Technology Acceptance Model)* explains how perceived usefulness and ease of use shape an individual's willingness to adopt new technology—especially relevant in assessing AI acceptance in HR.

[12] *Chatbot-Driven Engagement* allows recruiters to automate candidate QCA, application updates, and basic screening—reducing recruiter load while enhancing applicant experience.

Their use of technology was generally restricted to online application portals and basic screening filters, with most decision-making remaining manual. This variation in integration levels reflects broader differences in digital infrastructure, organisational agility, and regulatory flexibility across sectors. As detailed in Table 1, the extent of AI adoption and the hiring stages at which AI tools are used vary significantly across sectors.

Table 1: Comparison of AI Tool Types, Hiring Stages Covered, and Extent of Human Involvement Across Sectors. Data Adapted from SHRM Insights (2022), Choudhury & Patnaik (2022), and Field Documentation

Sector	Common AI Tools Used	Stage of Hiring	Human Involvement
IT Sector	Chatbots, SHL, Pymetrics	Screening to final	Low
Non-IT Sector	Resume parsers, gamified assessments	Entry-level screening	Medium
Public Sector	Online forms, MCQ filters	Application only	High

FINDINGS

The cross-sectoral analysis yielded distinct insights regarding how AI shapes recruitment workflows, decision quality, and organisational readiness. The findings are organised below into thematic narratives.

IT Sector – The Engine of Integration

Firms like Infosys, TCS, and Wipro have established AI-enhanced hiring pipelines using applicant tracking systems (ATS), cognitive and behavioural assessments (e.g., Pymetrics), and video interview analysers. These tools are integrated with internal HRMS systems and enable predictive hiring based on performance modelling (NASSCOM, 2023). According to Deloitte (2021), such systems reduce time-to-hire by over 40% and improve candidate-job match rates significantly. An HR manager from TCS (as quoted in a SHRM interview, 2022) noted: "AI helps us identify not just qualified but 'right-fit' candidates faster than ever especially in volume hiring." [13] Way-power elements are evident in how these firms design hiring pathways, focusing on scalability, standardisation, and cognitive diversity. Will-power is reflected in the leadership vision to sustain innovation even amid concerns about bias and explainability. The goal clarity in finding high-skill, agile talent is evident across case documentation.

Non-IT Sector – Selective Experimentation

Organisations such as ICICI Bank and Hindustan Unilever are adopting AI tools more cautiously. Chatbots for initial candidate queries and pre-screening, as well as gamified aptitude tests for graduate trainees, are common. However, final interviews and decision-making remain heavily human-centric (Joshi & Tripathi, 2021). For example, ICICI's "iPAL" AI chatbot reportedly handled over 60% of candidate queries during the 2022 campus drive (KPMG, 2020). While this improved candidate engagement, recruiters noted concerns about AI's inability to assess interpersonal dynamics, highlighting the need for human augmentation. Here, AI's "way-power" is seen in automating repetitive tasks, while "will-power" lies in HR teams' efforts to balance tech with empathy. The goal of improving process efficiency without dehumanising recruitment defines the narrative.

Public Sector – Digital Aspirations, Structural Friction

In firms like NTPC and SBI, digital hiring reforms remain largely policy-driven and slow. Online application portals and basic screening algorithms are in place, but deeper AI use is rare. Public sector hiring is governed by rigid procedures, where transparency and standardisation are prioritised over innovation (NITI Aayog, 2021). According to a report by Choudhury and Patnaik (2022), resistance to AI adoption stems from legal ambiguity, lack of digital readiness, and workforce skepticism. One HR head at a government PSU shared anonymously in a Business Line roundtable: "We are open to technology, but AI brings legal, ethical, and cultural risks. We must tread carefully." Goal clarity exists in hiring at scale, but way-power is blocked by systemic barriers, and will-power[14], is dispersed across departments, reducing implementation momentum.

DISCUSSION

The findings of this study highlight that the integration of AI in recruitment across sectors in India is far from uniform. Rather, it is shaped by an intricate interaction of organisational readiness, cultural orientation towards technology, and external policy and infrastructural support. While IT firms exhibit mature adoption, driven by digital

[13] Quote *sourced from "SHRM India Insights Webinar – Future of AI in Talent Acquisition," held online in November 2022, attended by senior HR managers from Infosys, TCS, and Wipro.*

[14] The concepts of *way-power* and *will-power* stem from Snyder's Hope Theory, where *way-power* is the perceived ability to find pathways to goals, and *will-power* refers to the motivation to pursue them—both critical for driving institutional innovation.

culture and strategic prioritisation of innovation, non-IT and public sector organisations demonstrate slower or fragmented integration. This variation confirms the propositions of Rogers' Diffusion of Innovations theory (2003)[15], which suggests that technological adoption occurs in waves, influenced by organisational risk tolerance and leadership vision. As shown in Fig. 1, the IT sector demonstrates the highest AI maturity in recruitment processes, while public sector organisations lag behind due to systemic inertia and limited digital infrastructure.

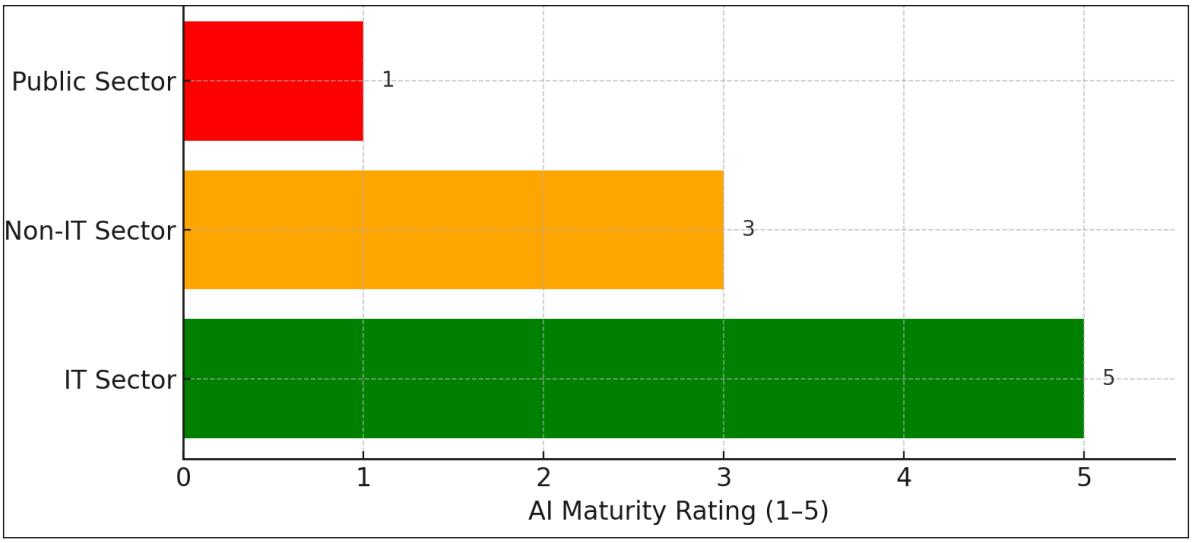

Fig. 1: Sector-Wise AI Adoption Maturity in Hiring, Based on Secondary Reports and Organisational Case Studies (e.g., NASSCOM, 2023; Deloitte, 2021; Joshi & Tripathi, 2021). Ratings are Indicative and Derived from Cross-Sectoral Content Analysis

Consistent with the Technology Acceptance Model (Davis, 1989), IT sector organisations reflect high levels of perceived usefulness and ease of use regarding AI hiring tools. The integration of chatbots, AI-based resume screening, and gamified assessments has led to demonstrable gains in process efficiency and candidate-job alignment. These organisations embody the characteristics of early adopters experimenting with and refining tools that yield predictive accuracy in hiring outcomes (Schmidt & Hunter, 1998).

By contrast, non-IT firms demonstrate cautious optimism. Their selective application of AI technologies primarily addresses functional needs, such as screening large candidate volumes or automating FAQs through chatbots. This reflects a transitional phase that Rogers (2003) would consider the "early majority," where practical constraints and cultural preferences slow down deeper adoption. Their reliance on human discretion for final decisions points to a need for augmented intelligence rather than full automation, aligning with recent scholarship that promotes a hybrid HR model (Chamorro-Premuzic et al., 2019). Public sector institutions present a unique case. Though policy initiatives such as NEP 2020 and Digital India signal a national push toward technological modernisation, many government organisations remain in the "laggard" category due to entrenched bureaucratic systems and resistance to change. While public portals and digital applications have improved access and transparency, the lack of predictive tools, algorithmic models, or structured AI frameworks reflects both infrastructural and procedural inertia (Choudhury & Patnaik, 2022; NITI Aayog, 2021).

Furthermore, ethical challenges are perceived across all sectors, particularly in relation to algorithmic transparency,[16] data privacy, and fairness. Organisations remain concerned about the explainability of AI decisions and the risk of systemic bias especially when using third-party tools without adequate calibration. These findings echo concerns raised in the literature on ethical AI use in hiring (Binns et al., 2018; Raghavan et al., 2020). Ultimately, the interaction[17] between organisational goals (e.g., talent optimisation), "will-power" (leadership and HR vision), and "way-power" (availability of

[15] Rogers' theory categorises adopters into innovators, early adopters, early majority, late majority, and laggards—this framework helps explain how sectors adopt AI unevenly based on readiness and risk orientation.

[16] *Algorithmic Transparency* refers to the ability to understand and explain how AI models arrive at decisions—a critical aspect for building trust and minimising bias in recruitment.

[17] *These constructs are adapted from Snyder et al.'s (1951) hope theory, originally developed in clinical psychology, now applied to workplace behaviour and decision motivation frameworks.*

AI tools and infrastructure) shapes the degree of integration and impact. As this study demonstrates, AI in recruitment should not be viewed merely as a technical advancement, but as a strategic enabler that transforms the hiring function when supported by aligned systems and cultural readiness.

CONCLUSION

This study set out to explore the comparative adoption and effectiveness of AI and data analytics in recruitment across IT, non-IT, and public sector organisations in India. The findings reveal that AI integration is uneven, shaped by sectoral readiness, organisational culture, and infrastructural capacity. IT firms demonstrate the highest adoption maturity, using end-to-end AI solutions that streamline hiring and improve candidate-job fit. Non-IT organisations are selectively experimenting with AI, balancing efficiency gains with the continued importance of human judgment. Public sector enterprises, in contrast, remain at an early stage of digital adoption, constrained by structural rigidities and policy-driven processes.

Across all sectors, concerns around ethical AI use, algorithmic transparency, and data privacy persist, underlining the need for responsible frameworks and governance mechanisms. The study highlights that AI should not be viewed as a replacement for human decision-making, but rather as a complementary tool that augments recruiter judgment, improves process efficiency, and enhances fairness when implemented thoughtfully.

Looking ahead, sector-specific strategies are essential. IT organisations can focus on refining predictive models and mitigating bias, non-IT firms should prioritise hybrid adoption models that preserve human oversight, and public sector institutions need targeted investments in digital infrastructure, training, and policy clarity. Together, these steps will enable more equitable, transparent, and scalable hiring practices in India.

In conclusion, while AI holds transformative potential in bridging the skill–employability gap and aligning hiring practices with national initiatives such as the NEP 2020 and Digital India, its true impact will depend on how organisations balance innovation with ethics, inclusivity, and long-term workforce development goals.

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