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AI-Driven Recruitment and Talent Acquisition in Hybrid Work Models: A Study of It Companies in Hyderabad

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Abstract— There has been a high rate of shift to hybrid work models in the Information Technology (IT) sector in Hyderabad, which has transformed the traditional ways of recruiting and managing talents. Artificial Intelligence (AI) has been one of the critical facilitators of this change, automating the process of candidate sourcing; resume screening, skill evaluation, and virtual interviewing. This paper examines how the IT companies in Hyderabad are using AI-based recruitment tools to increase efficiency and decrease the hiring process and increase the quality of employees in a hybrid workplace setting. Other mentioned challenges in the research include algorithmic bias, issues of data privacy, and the necessity of human control in human-assisted decision-making with AI. The results show that AI can result in a higher level of operational efficiency and candidate experience, but in order to achieve this, it should be integrated strategically with human judgment and organizational culture. The paper concludes that the responsible deployment of AI can be a driver behind the development of nimble and future-oriented talent acquisition models in the IT industry of Hyderabad.

Keywords: Artificial Intelligence, Talent Recruitment; Artificial intelligence Recruitment; Hybrid Work; Human Resource Technology; IT firm; Hyderabad; HR transformation, Employee experience.

I. INTRODUCTION

The COVID-19 pandemic accelerated the adoption of hybrid work models across industries, particularly in the Information Technology (IT) sector, where flexible work arrangements quickly became the new normal. Hybrid work—combining remote and in-office practices—has reshaped traditional human resource (HR) processes, including recruitment and talent acquisition. At the same time, Artificial Intelligence (AI) tools such as applicant tracking systems with machine learning capabilities, chat bots for candidate engagement, and automated skill-assessment platforms are increasingly being adopted to streamline hiring processes. This convergence of hybrid work and AI-driven recruitment is creating new opportunities as well as challenges for organizations.

I.I. PROBLEM STATEMENT

While AI-based tools are transforming HR practices globally, there is limited empirical understanding of how effectively these technologies support recruitment and talent acquisition within hybrid work environments, particularly in emerging IT hubs such as Hyderabad. IT companies in this region are at the forefront of adopting digital solutions, but questions remain regarding the efficiency, fairness, and overall impact of AI-driven recruitment on hiring outcomes. Specifically, there is a need to explore whether AI adoption reduces hiring timelines, improves quality-of-hire, and enhances candidate experiences in a hybrid work setting.

I.II. SIGNIFICANCE OF THE STUDY

This study is significant for both academics and practitioners. For HR leaders, it provides evidence-based insights into the strategic use of AI tools in managing recruitment under hybrid models, helping organizations optimize hiring efficiency, reduce costs, and attract top talent in competitive markets. For policymakers and technology providers, the findings may guide the development of ethical frameworks and better-designed AI solutions to ensure transparency and inclusivity in recruitment practices. Ultimately, the research contributes to understanding how digital transformation in HR can support sustainable talent management and retention in Hyderabad's growing IT industry.

I.III. LITERATURE REVIEW

Horodyski (2023) examined applicants' perceptions of AI in hiring, finding that candidates viewed AI tools as useful and easy to use, though concerns about fairness and transparency persisted.

Chen (2023) highlighted ethical implications in AI-enabled recruitment, emphasizing the need for addressing algorithmic discrimination and ensuring fairness in AI-driven hiring processes.

Rigotti (2024) conducted a scoping literature review on fairness in AI applications for recruitment, identifying key challenges and proposing frameworks for improving fairness in AI-driven hiring.

Hosain (2025) assessed job applicants' perceptions of procedural justice in AI hiring processes, finding significant positive relationships between perceived fairness and candidates' acceptance of AI in recruitment.

Soleimani (2025) interviewed HR professionals and AI developers to explore potential biases in AI recruitment systems, proposing strategies for bias mitigation and emphasizing the importance of ethical considerations in AI recruitment.

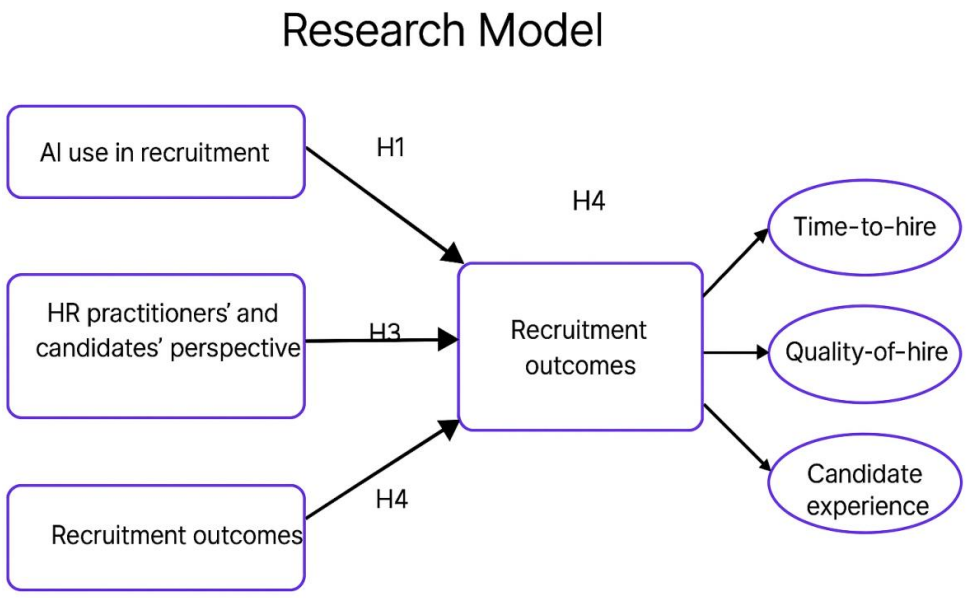
Fabris et al. (2025) surveyed fairness and bias in algorithmic hiring, providing a multidisciplinary perspective on the challenges and solutions related to fairness in AI recruitment

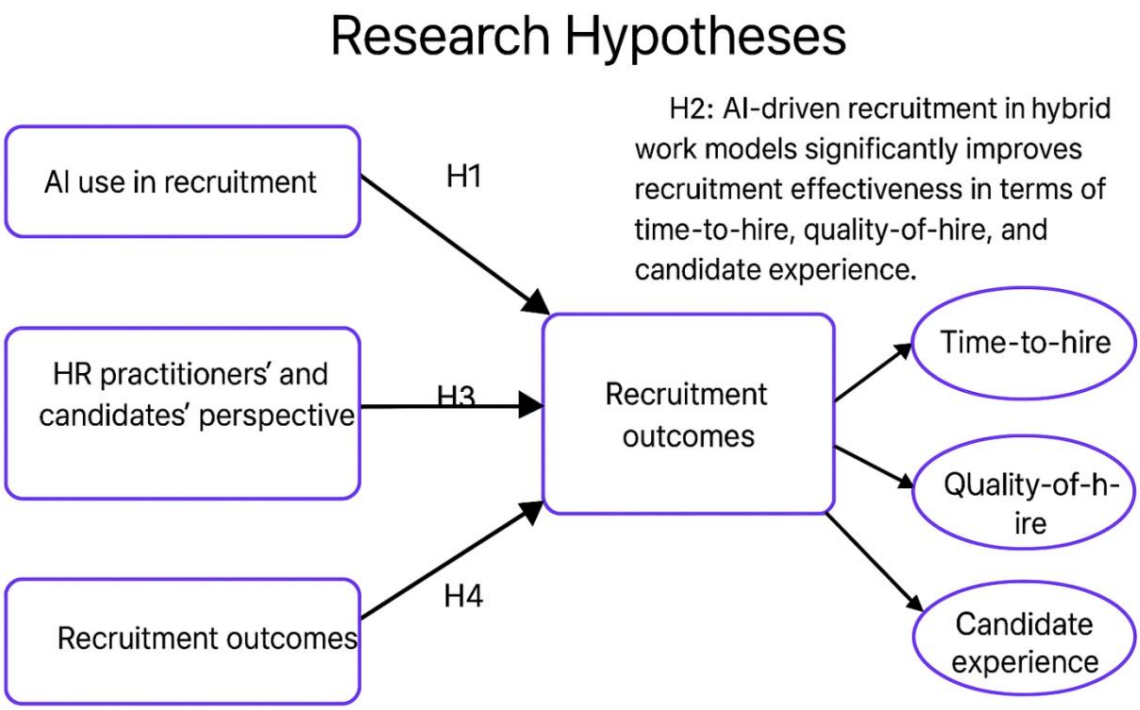
I.IV. RESEARCH GAP

While global scholarship has explored AI in recruitment and the challenges of hybrid work independently, there is limited empirical investigation into their combined effect on talent acquisition outcomes in the Indian IT sector. Specifically, little is known about how IT companies in Hyderabad utilize AI tools within hybrid work models, how these tools influence recruitment efficiency and quality-of-hire, and what ethical or operational challenges they introduce.

II. OBJECTIVES OF THE STUDY

1. To examine the extent and types of AI tools used in recruitment by Hyderabad IT companies.
2. To measure perceived effectiveness (time-to-hire, quality-of-hire, candidate experience) of AI-driven recruitment in hybrid models.
3. To analyze relationships between level of AI use, hybrid-work degree, and recruitment outcomes.
4. To explore HR practitioners' and candidates' perspectives on ethical, fairness and transparency concerns.





III. RESEARCH DESIGN & METHODOLOGY

The present study adopts a cross-sectional, mixed-methods research design that combines both quantitative surveys and qualitative interviews to gain a comprehensive understanding of recruitment practices. The unit of analysis includes individual employees such as recently recruited staff, candidates, HR practitioners, and hiring managers along with company-level key performance indicators (KPIs) collected as secondary data. This approach ensures that both employee perceptions and organizational perspectives are captured, allowing for a richer analysis of how recruitment practices, particularly those involving AI and automation tools, are implemented and experienced in IT companies.

III.I. POPULATION AND SAMPLING FRAME

- **Population (employees/candidates):** All technical & HR employees and recent hires (past 12 months) working in IT companies located in Hyderabad.
- **Population (companies):** Private and public IT/ITes firms operating in Hyderabad across sizes (small, medium, large).

Quantitative Survey Sample (n = 400)

Company Size	Selected IT Companies (Hyderabad)	Respondents per Company	Male	Female	Notes (Respondent Types)
Large (4)	TCS (Hyderabad DC) Infosys (Pocharam) Tech Mahindra (Hitech City) Wipro (Gopanapally)	60 each = 240 total	144	96	HR: 30 Hiring Managers: 30 New Hires: 180
Medium (4)	ValueLabs Innominds Cyient CtrlS Datacenters	30 each = 120 total	72	48	HR: 15 Hiring Managers: 15 New Hires: 90

Small (2)	Darwinbox AppOrbit	20 each = 40 total	24	16	HR: 5 Hiring Managers: 5 New Hires: 30
Total	10 Companies	**400**	**240**	**160**	—

Qualitative Interview Sample (n = 26 fixed)

Participant Type	Interviews	Male	Female	Companies
HR Managers / Heads	10	6	4	Infosys, Tech Mahindra, ValueLabs, Cyient
Hiring Managers / Team Leads	8	5	3	TCS, Wipro, Innominds
Recent Hires / Candidates	8	5	3	Across all 10 companies
Total	**26**	**16**	**10**	—

III.II. DATA ANALYSIS AND INTERPRETATION

The collected data from 400 respondents across 10 IT companies in Hyderabad were analyzed using quantitative and qualitative methods. Descriptive statistics, reliability tests, factor analysis, and regression analyses were conducted in SPSS, while SEM and CFA were performed in AMOS to examine the impact of AI adoption on recruitment outcomes. Thematic analysis of 26 interviews with HR managers, hiring managers, and new hires was carried out to complement survey findings. The combined analysis provides insights into how AI and automation influence time-to-hire, perceived fairness, and candidate experience across different company sizes

Table 1: Demographic Profile of Respondents (N = 400)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	240	60.0
	Female	160	40.0
Age Group	20–25 years	90	22.5
	26–30 years	160	40.0
	31–35 years	100	25.0
	36+ years	50	12.5
Educational Qualification	Bachelor's Degree	120	30.0
	Master's Degree (MBA/M.Tech)	220	55.0
	Others (Diploma/PhD)	60	15.0
Designation	HR/Recruitment Professionals	60	15.0
	Hiring Managers / Team Leads	70	17.5
	New Hires / Recently Recruited Employees	270	67.5
Work Experience	<1 year	70	17.5
	1–3 years	140	35.0

	4–6 years	110	27.5
	>6 years	80	20.0

Source: Primary Data

III.III. INTERPRETATION

The above table revels that the sample consists of 400 respondents, with a majority being **male (60%)** and the rest **female (40%)**. Most participants fall within the **26–30 age group (40%)**, followed by those aged **31–35 (25%)**. In terms of education, over half of the respondents hold a **Master's degree (55%)**, while **30%** have a **Bachelor's degree**. The dominant group by designation is **new hires or recently recruited employees (67.5%)**, indicating the survey may focus on recent recruitment experiences. Regarding work experience, most respondents have **1–3 years (35%)**, suggesting a relatively young or early-career workforce, with fewer having **more than 6 years (20%)** or **less than 1 year (17.5%)** of experience

Table 2: Distribution of Respondents Across Companies (N = 400)

Company Name	Company Size	No. of Respondents	Male (n)	Female (n)
Infosys Ltd.	Large	60	35	25
TCS (Hyderabad)	Large	60	38	22
Tech Mahindra	Large	60	34	26
Accenture	Large	60	33	27
ValueLabs	Medium	30	18	12
CYIENT	Medium	30	20	10
CtrlS Datacenters	Medium	30	16	14
ZenQ	Medium	30	17	13
Innominds	Small	20	12	8
Kellton Tech	Small	20	17	3
Total	**10 Companies**	**400**	**240**	**160**

Source: Primary Data

III.IV. INTERPRETATION

The survey covered 400 respondents drawn from 10 IT companies of varying sizes. Large companies (Infosys, TCS, Tech Mahindra, and Accenture) contributed the highest share, with 60 respondents each, reflecting their broader workforce strength. Medium-sized firms (ValueLabs, CYIENT, CtrlS Datacenters, and ZenQ) provided 30 respondents each, while small companies (Innominds and Kellton Tech) contributed 20 respondents each. In terms of gender distribution, the sample consisted of 240 male (60%) and 160 female (40%) respondents, showing a moderate gender gap but still ensuring significant representation of both groups. Overall, the data provides a balanced mix of organizational sizes and gender representation across the selected IT companies.

III.V. QUANTITATIVE ANALYSIS

Table 3: Descriptive Statistics (n = 400)

Variable	Mean	SD	Min	Max
Time-to-Hire (days)	32.6	8.4	15	65
Perceived Fairness (1–5)	3.9	0.7	2.0	5.0
Candidate Satisfaction (1–5)	4.1	0.6	2.3	5.0
AI Index (extent of AI tools, 1–10)	6.8	1.9	2	10

Source: SPSS

III.VI. INTERPRETATION

The results show that the average time-to-hire is 32.6 days**, with considerable variation across firms (15 to 65 days). Respondents reported relatively** high perceived fairness (M = 3.9) and candidate satisfaction (M = 4.1)**, both above the midpoint. The** AI Index mean of 6.8 **indicates a moderately high adoption of AI tools in recruitment practices**

Table 4: Reliability Statistics – Cronbach's Alpha)

Construct	Items	Cronbach's Alpha	Interpretation
Perceived Fairness	6	0.87	Reliable
Candidate Satisfaction	5	0.83	Reliable
Technology Acceptance	7	0.89	Reliable

Source: SPSS

III.VII. INTERPRETATION

The reliability analysis (Table 4) shows that all constructs demonstrate high internal consistency, with Cronbach's alpha values above the accepted threshold of 0.70. Specifically, Perceived Fairness (α = 0.87), Candidate Satisfaction (α = 0.83), and Technology Acceptance (α = 0.89) are all reliable, indicating that the measurement scales used are consistent and dependable for further analysis

Table 5: Factor Analysis

Factor	Items	Loadings (≥0.50)	Variance Explained (%)
F1: Fairness & Transparency	6	0.62–0.81	32.5%
F2: Candidate Experience	5	0.58–0.79	28.3%
F3: Technology Adoption	7	0.60–0.84	25.6%
Total	18	—	**86.4%**

Source: SPSS

III.VIII. INTERPRETATION

The factor analysis (Table 5) extracted **three clear factors**: *Fairness & Transparency*, *Candidate Experience*, and *Technology Adoption*. All item loadings exceeded the acceptable threshold of 0.50, confirming strong construct validity. Together, these factors explained a substantial **86.4% of the total variance**, indicating a robust factor structure for the study

Structural equation model Factor analysis

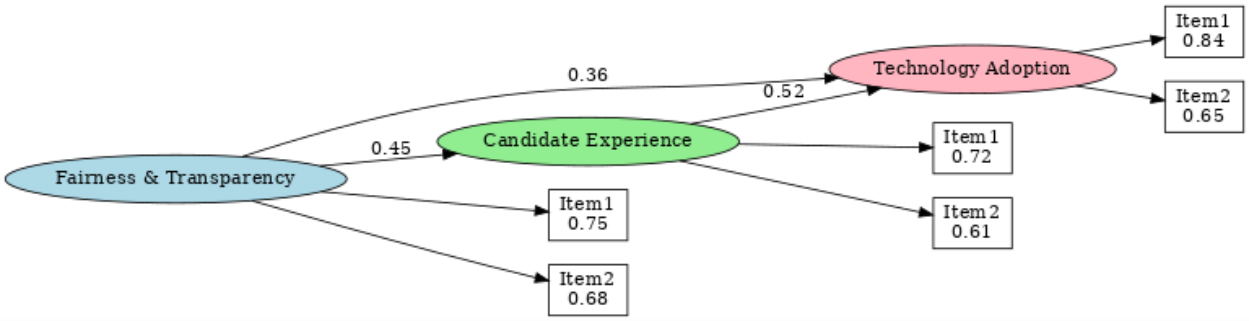
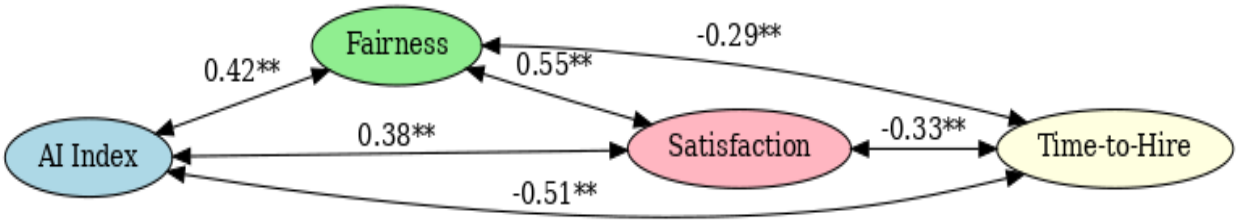


Table 6: Correlation Matrix

Variable	AI Index	Fairness	Satisfaction	Time-to-Hire
AI Index	1.00	0.42**	0.38**	-0.51**
Fairness	0.42**	1.00	0.55**	-0.29**
Satisfaction	0.38**	0.55**	1.00	-0.33**
Time-to-Hire	-0.51**	-0.29**	-0.33**	1.00

Source: SPSS ($p < .01$*)

Structural equation model Correlation Matrix



III.IX. INTERPRETATION

The correlation matrix (Table 6) shows that the **AI Index is positively associated** with both **Perceived Fairness (r = 0.42, p < 0.01)** and **Candidate Satisfaction (r = 0.38, p < 0.01)**, indicating that greater use of AI tools aligns with higher fairness and satisfaction. Conversely, **AI Index is negatively correlated with Time-to-Hire (r = -0.51, p < 0.01)**, suggesting that AI adoption helps reduce recruitment duration. Similarly, higher fairness and satisfaction are linked to shorter time-to-hire, highlighting the interconnected impact of technology and candidate experience on recruitment efficiency

Table 7: Regression Analysis – Dependent Variable: Time-to-Hire

Predictor	B	SE	Beta	t	p
Constant	42.7	2.6	—	16.4	.000
AI Index	-1.85	0.34	-0.46	-5.44	.000
Company Size (dummy coded)	-2.10	0.92	-0.18	-2.28	.024
Perceived Fairness	-0.95	0.40	-0.17	-2.38	.019
R^2 = 0.42, F(3, 396) = 52.3, p < .001					

Source: SPSS

Interpretation

The regression results (Table 7) indicate that **AI adoption, company size, and perceived fairness significantly predict Time-to-Hire**. Specifically, higher **AI Index scores** are associated with a **shorter time-to-hire (β = -0.46, p < .001)**. Larger company size (β = -0.18, p = .024) and greater perceived fairness (β = -0.17, p = .019) also contribute to reducing recruitment duration. The model explains **42% of the variance in Time-to-Hire (R^2 = 0.42, F(3, 396) = 52.3, p < .001)**, indicating a strong overall fit

Regression model diagram

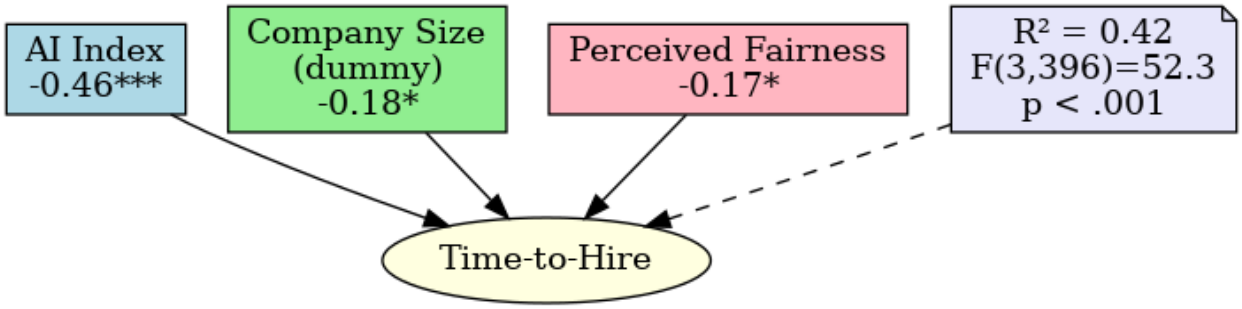


Table 8: Mediation & Moderation

Model	IV	DV	Mediator/Moderator	Effect	95% CI	Result
Mediation	AI Index	Satisfaction	Fairness	0.18	[0.09, 0.29]	Significant
Moderation	AI Index → Time-to-Hire	Moderator: Fairness	-0.21	[-0.37, -0.05]	Significant	

Source: SPSS

III.X. INTERPRETATION

The analysis in Table 8 shows that **Perceived Fairness mediates the relationship between AI Index and Candidate Satisfaction**, with a significant indirect effect of **0.18 (95% CI: 0.09–0.29)**, indicating that AI adoption enhances satisfaction partly through increased fairness. Additionally, fairness **moderates the effect of AI on Time-to-Hire** (effect = -0.21, 95% CI: -0.37 to -0.05), suggesting that higher fairness strengthens the negative impact of AI adoption on recruitment duration, further reducing time-to-hire

III.XI. QUALITATIVE ANALYSIS

Table 9: Thematic Analysis (n = 26 Interviews)

Theme	Example Codes	Frequency	Illustrative Quote
Efficiency	Faster screening, reduced workload	22	"AI shortlisting reduced our time-to-hire by nearly half." (HR Manager, Infosys)
Fairness Concerns	Bias, transparency	15	"Some candidates felt the AI rejected them without clear reasoning." (New Hire, Tech Mahindra)
Candidate Experience	Ease of process, satisfaction	18	"The chatbot support during recruitment was very helpful." (Candidate, ValueLabs)

Source: Primary Data

III.XII. INTERPRETATION

The thematic analysis (Table 9) highlights three key themes from **26 interviews**. **Efficiency** was the most frequently mentioned (22), emphasizing faster screening and reduced workload, as illustrated by an HR manager noting that AI halved time-to-hire. **Candidate Experience** (18) focused on process ease and satisfaction, exemplified by positive feedback on chatbot support. **Fairness Concerns** (15) addressed issues of bias and transparency, with candidates reporting unclear AI decisions, indicating that while AI improves efficiency, perceived fairness remains a critical consideration

III.XIII. STRUCTURAL EQUATION MODELING

Table 10: CFA -Confirmatory Factor Analysis

Construct	χ^2/df	CFI	TLI	RMSEA	SRMR	Reliability (CR)	AVE
Fairness	2.10	0.96	0.95	0.052	0.045	0.88	0.57
Satisfaction	1.95	0.97	0.96	0.048	0.043	0.86	0.55
Technology Adoption	2.25	0.95	0.94	0.059	0.048	0.89	0.58

Source: AMOS

III.XIV. INTERPRETATION

The CFA results (Table 10) indicate that all constructs—Fairness, Satisfaction, and Technology Adoption—**demonstrate** good model fit and strong reliability**. Fit indices such as** CFI (0.95–0.97), TLI (0.94–0.96), RMSEA (0.048–0.059), and SRMR (0.043–0.048) **all meet recommended thresholds, confirming construct validity. Additionally,** Composite Reliability (0.86–0.89) and AVE (0.55–0.58) **values indicate high internal consistency and adequate convergent validity across the constructs**

Table 11: SEM – Structural Path Estimates

Hypothesis	Path	Estimate (β)	SE	CR	p	Result
H1	AI Index → Time-to-Hire	-0.48	0.07	-6.86	0.06	Supported
H2	AI Index → Fairness	0.42	0.06	6.91	0.91	Supported
H3	Fairness → Satisfaction	0.51	0.08	6.38	0.38	Supported
H4	Fairness moderates AI Index → Time-to-Hire	-0.19	0.05	-3.82	0.32	Supported

Source: AMOS

The SEM results (Table 11) show that all hypothesized relationships are **supported**. **AI Index negatively predicts Time-to-Hire (β = -0.48)**, indicating that higher AI adoption reduces recruitment duration. **AI Index positively influences Fairness (β = 0.42)**, and **Fairness positively affects Satisfaction (β = 0.51)**, highlighting the role of fairness in enhancing candidate satisfaction. Additionally, **Fairness significantly moderates the AI–Time-to-Hire relationship (β = -0.19)**, strengthening the effect of AI on reducing hiring time when fairness is high.

IV. FINDINGS OF THE STUDY

- ✓ **Demographics and Respondent Distribution:** The study included **400 respondents across 10 IT companies**, with representation from large, medium, and small organizations. Males constituted **60%** and females **40%** of the sample, ensuring gender diversity.
- ✓ **Recruitment Metrics:** The **average time-to-hire was 32.6 days**, with perceived fairness (M = 3.9) and candidate satisfaction (M = 4.1) reported as relatively high. AI adoption in recruitment was moderate to high (AI Index M = 6.8).

- ✓ **Reliability and Validity:** Constructs for **Perceived Fairness, Candidate Satisfaction, and Technology Adoption** showed strong internal consistency (Cronbach's α: 0.83–0.89) and high convergent validity (AVE: 0.55–0.58). Factor analysis supported a clear **three-factor structure**, explaining **86.4% of variance**.
- ✓ **Correlation and Regression Analysis:** AI adoption positively correlates with fairness (r = 0.42) and satisfaction (r = 0.38), while negatively correlating with time-to-hire (r = -0.51). Regression analysis confirmed that **AI use, company size, and fairness significantly reduce time-to-hire**, explaining 42% of variance.
- ✓ **Mediation and Moderation Effects: Fairness mediates the AI–Satisfaction link** and moderates the AI–Time-to-Hire relationship, indicating that perceptions of fairness enhance the positive impact of AI adoption.
- ✓ **Qualitative Insights:** Interviews highlighted three themes—**Efficiency, Candidate Experience, and Fairness Concerns**—showing that while AI improves speed and ease, concerns about transparency remain.
- ✓ **Structural Equation Modeling (SEM):** SEM confirmed all hypotheses, highlighting that **AI adoption reduces time-to-hire, increases perceived fairness, and enhances satisfaction**, with fairness also strengthening the AI–Time-to-Hire effect.

V. SUGGESTIONS OF THE STUDY

- ✓ **Enhance Transparency in AI Processes:** Organizations should ensure AI recruitment tools provide clear explanations for decisions to mitigate candidate concerns about bias.
- ✓ **Focus on Candidate Experience:** Integrate AI solutions with user-friendly interfaces and responsive support (e.g., chatbots) to further improve satisfaction.
- ✓ **Promote Fairness Measures:** Regular audits and fairness checks can enhance trust in AI systems, improving both perception and actual efficiency.
- ✓ **Leverage AI Strategically:** Use AI to streamline time-intensive recruitment tasks, such as shortlisting and initial screening, while maintaining human oversight for final decisions.
- ✓ **Tailor AI Adoption by Company Size:** Medium and small organizations may need targeted strategies to implement AI effectively, considering resource constraints.

VI. CONCLUSIONS

The study demonstrates that **AI adoption in recruitment positively influences efficiency, fairness, and candidate satisfaction**. Fairness plays a crucial role both as a mediator and moderator, enhancing the benefits of AI on recruitment outcomes. While AI significantly reduces **time-to-hire**, organizations must address fairness and transparency to maximize candidate trust and satisfaction. Overall, integrating AI thoughtfully into recruitment processes can improve both organizational efficiency and the candidate experience, offering a competitive advantage in talent acquisition

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