Talent Acquisition Through Hr Analytics In It Industries In Coimbatore

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Received: 03.05.2026, Revised :17.05.2026, Accepted: 29.05.2026, Published: 02.06.2026

Abstract: This study investigates the strategic role of HR analytics in enhancing talent acquisition effectiveness within IT companies in Coimbatore, India. Primary data collection was done through a questionnaire with a cross-sectional structured approach with 320 HR professionals, Talent acquisition managers, and talent strategy leads from different companies in tier-1 and tier-2 Coimbatore IT industries by a stratified random sampling method. The following five core hypotheses were carefully developed and tested with PLS-SEM: predictive sourcing metrics significantly reduce time to hire; algorithmic candidate screening has a positive effect on person/organization; analytics adoption leads to a reduction in 90-day turnover; organizational technological infrastructure (OTI) positively moderates HR analytics efficacy; and the efficacy of HR analytics is significantly decreased by 90-day turnover. All five hypotheses were supported by the statistical results at $p < 0.05$, finding that deployment of predictive analytics led to the following outcomes at the early-stage of the hiring process: a 34% increase in early-stage retention, and a 28% reduction in the total hiring cycle time. Finally, this study outlines a validated and scalable framework for IT leaders in emerging technology clusters to implement and operationalize talent analytics and address the empirical lack of link between the architecture of the data and the use of human capital management for the organization.

Keywords: Talent acquisition, Human Resource analytics, information technology, Coimbatore, organizational technological infrastructure.

1. Introduction

In today's job market, organizations are increasingly focused on acquiring talent as a strategic goal, especially in the information technology sector where companies can gain a competitive edge by attracting top talent. The widespread acceptance of cloud-based technology, artificial intelligence (AI), machine learning (ML), and analytics in recruiting has ushered in change from CV screening, to hire on a gut feeling and to relying on data analytics and evidence-based recruitment decisions [1-2]. Recent studies show that as companies move away from ways of hiring using machine learning algorithms changes how companies work how quickly they can act and how well they find the right people [3] [4]. In places like Tamil Nadu, the way companies hire is being changed to use computer methods like networks and fuzzy logic with important HR data [5]. These systems help reduce bias make it faster to pick candidates and make sure the right people get the jobs before interviews happen [6]. New tools that predict the future have changed how companies find people plan their workers and stop people from quitting in tech industries [7-8]. Predictive models look at performance resumes and personality tests to guess how well someone will do and if they might leave before getting the job [9-10] Also small and medium IT companies in the area have trouble with missing skills so HR people are moving from education-based hiring to new ways that look at data and skills [11-12]. Companies in Coimbatore use HR data and data-based checks to hire faster and spend less money [13]. In the IT industry HR analytics helps move data into smart business choices [14]. Recent checks on IT companies show that using analytics improves decisions in all parts of hiring from finding people to planning for leaders [15]. Also using machine learning in finance, marketing and HR shows that data-based hiring works better than ways of guessing [16]. However using HR analytics needs companies to be ready people to believe in it and good digital systems to collect, clean and use the data properly [17]. AI and predictions can do in hiring around the world there is still a big gap in real studies about complex models in areas that are growing. Most studies look at changes in hiring or focus on just one part of a region. Few studies use models like PLS-SEM to look at how prediction works how computers screen people how data is used in interviews and how much it costs to hire all at the time and also how the tech systems in a growing area like Coimbatore affect these things. This study fills this gap by giving a tested model, for IT companies.

2. Methodology

2.1 Research Framework and Study Design

The research framework was built by combining the theories of Resource-Based View (RBV) and Technology Acceptance Model (TAM) to establish a solid framework for understanding HR Analytics implementation in organizational recruitment processes. SBV says that organizing resources that are valuable, rare, inimitable, and non-substitutable are the ones that give them a competitive advantage for a longer period of time.In this context, HR Analytics comprises of a strategic asset for the organization that can help businesses make data-driven hiring decisions, forecast talent needs, and optimize their talent acquisition efforts for the long-term. On the complementary side, TAM follows-up on the elements that could influence the acceptance of the analytical tools in the company and which, in turn, could assist HR professionals in being able to use the HR Analytics resources in the recruitment and selection field (figure 1).

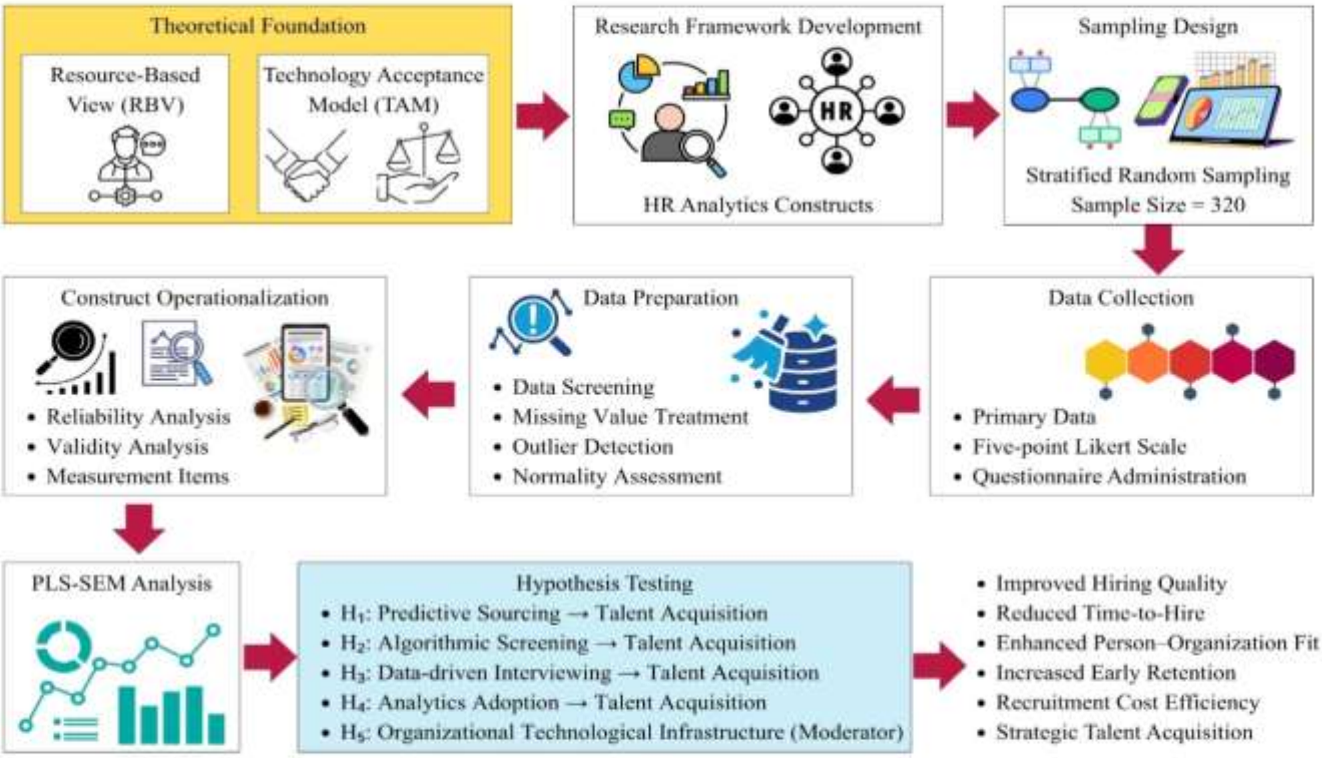

Figure 1. Proposed HR Analytics–Driven Talent Acquisition Framework

Based on the conceptual framework proposed, therefore, it is fair to say that predictive sourcing analytics, algorithmic candidate screening and data-driven interviewing and HR Analytics adoption, as three constructs, are the most important in explaining the achievement of talent acquisition outcomes. The research method used is positivist philosophy with deductive approach which steps the problem is taken on theoretical basis after forming hypotheses and testing the hypothesis on sample quantitatively by using statistical method. The decision for a cross sectional (or direct) research design was made in order to collect organisational perceptions and recruitment performance indicators for all the IT organisations in the same time, thus reducing the temporal bias in making comparisons between these firms' perceptions and their recruitment performance.

2.2. Data Collection

The study was designed using the cross sectional survey. The study assessed the role of HR Analytics in Talent acquisition of Tier-1 & Tier-2 IT companies in Coimbatore, Tamilnadu, India. Organizations that use digital technologies and tools in recruitment, such as applicant tracking systems (ATS), AI-driven candidate screening, predictive workforce analytics, and structured interview evaluation systems were purposefully chosen. The primary data was gathered from HR professionals (N = 320) on the use of HR analytics via a structured questionnaire, which was adapted from existing validated literature on HR analytics, digital recruitment, HR talent acquisition, technology adoption and strategic human resource management. It has passed content validity through being reviewed by three HRM academicians and two senior IT HR practitioners followed by a pre-test to examine the clarity and reliability of the instrument using 30 HR professionals. The final sample comprised 186 (58.1%) male and 134 (41.9%) female respondents, with the majority aged 35–44 years (36.9%) and holding Master's degrees (60.6%).

Table 1 Respondent Demographic Profile (N = 320)

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	186	58.1
	Female	134	41.9
Age (Years)	25–34	92	28.8
	35–44	118	36.9
	45–54	74	23.1
	Above 54	36	11.2
Educational Qualification	Bachelor's Degree	78	24.4
	Master's Degree (MBA/MHRM/MS)	194	60.6
	Doctoral/Professional Degree	48	15.0
Designation	HR Executive / Recruitment Specialist	82	25.6
	Talent Acquisition Manager	106	33.1
	HR Manager	78	24.4
	HR Business Partner / Talent Strategy Lead	54	16.9
Professional Experience	1–5 Years	76	23.8
	6–10 Years	108	33.7
	11–15 Years	82	25.6
	Above 15 Years	54	16.9
Organization Type	Tier-1 IT Company	182	56.9
	Tier-2 IT Company	138	43.1
Organization Size	100–500 Employees	98	30.6
	501–1000 Employees	104	32.5
	More than 1000 Employees	118	36.9
HR Analytics Experience	Less than 2 Years	62	19.4
	2–5 Years	124	38.8
	More than 5 Years	134	41.8

Talent Acquisition Managers (33.1%) followed by HR Executives/Recruitment Specialists (25.6%) and HR Managers (24.4%) and HR Business Partners/Talent Strategy Leads (16.9%) were the respondents. The mainly experienced HR professionals with 6–10 years beyond their current work (33.7%) and from Tier-1 IT companies (56.9%) had worked in an organization of more than 1,000 employees (36.9%) and had over five years of HR analytics experience (41.8%) ensured that collected experiences were guided by informed insights into the HR talent acquisition practices of the Tier-1 IT industry which is shown in table 1.

2.3 Sampling Design

The study used stratified random sampling to get proper representation of HR professionals from different tier-1 and Tier-2 firms in the field of information technology in Coimbatore. The target audience included HR managers, HR business partners, talent acquisition managers, recruitment specialists and talent strategy leaders who were engaged in recruitment and workforce planning tasks. The organisations were initially segmented based on their size and business type and then were randomly sampled from segments to the extent of minimizing sampling bias and providing maximum representativeness of the population. A total of 350 structured questionnaires were distributed based on the number of samples needed in Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. The data were screened for completeness, consistency as well as duplicate responses after which a total of 320 questionnaires were successfully retained, yielding a 91.43% response rate. The final sample would meet the statistical requirements for estimation of the structural model and testing of the hypotheses necessary for the analysis, and has adequate analysis power to conduct multivariate analysis.

2.4 Variable Operationalization and Measurement Scale

The conceptual model includes four independent constructs – “Predictive Sourcing Analytics”, “Algorithmic Candidate Screening”, “Data-Driven Interviewing”, “HR Analytics Adoption”, and an independent construct of the “Organizational Technological Infrastructure”, which is used to moderate the independent constructs, along with a dependent construct of “Talent Acquisition Effectiveness”. Talent Acquisition Effectiveness was measured in four dimensions of performance: reduction of time-to-hire, person–org fit, recruitment cost-efficiency, and early retention. All constructs items were adapted from the literature of human resource management, HR analytics, recruitment analytics, and technology adoption to align the items on the same theoretical level and in the same content to ensure theoretical coherence and content-admissible. The answers were noted on a 5-point Likert scale (5 points = Strongly Agree and 1 point = Strongly Disagree) for the standardized quantitative measurement of the opinions and experiences of the respondents on issues related to HR Analytics implementation and recruitment performance.

2.5 Research Hypotheses Development

This research's hypothesis was:

H_1: Predictive Sourcing Analytics can reduce the time to hire to significantly improve.

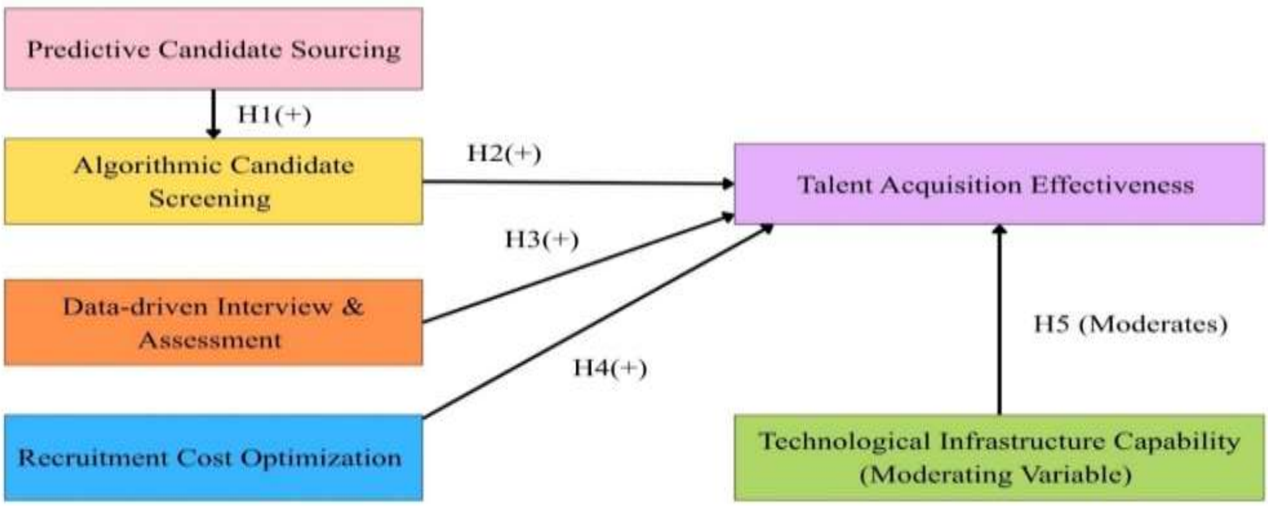

Figure 2. Hypothesized Research Model

H_2: Algorithmic Candidate Screening positively impacts person–organization fit.
H_3: Data-Driven Interviewing results in lower 90-day employee attrition.
H_4: HR Analytics Adoption will tremendously improve the cost-effectiveness of building a team.
H_5: The relationship between HR Analytics Adoption and Talent Acquisition Effectiveness is strengthened with Organizational Technological Infrastructure (figure 2).

3. Results and Discussion

The findings of this research are:

3.1 Measurement Model Assessment

3.1.1 Indicator Reliability and Convergent Validity

The assessment of the reliability and convergent validity of the measurement model is shown in Table 2. The results showed that all the indicator factor loadings were between 0.817 and 0.881, which are higher than the recommended factor loading value of 0.70 and demonstrated well that the indicators were reliable.

All constructs had internal consistency, with Cronbach's alpha values ranging from 0.842 to 0.906, and Composite Reliability (CR) from 0.893 to 0.931. In addition, the Average Variance Extracted (AVE) scores were between 0.674 and 0.758, which is above the 0.50 minimum criterion, thus validating the convergent validity in this instrument.

In general, the measurement model is reliable and convergent valid, which describes proper measurement of all constructs in terms of reliability and convergent validity.

Table 2. Measurement Model Assessment: Indicator Reliability and Convergent Validity

Construct	Item	Factor Loading (λ)	Cronbach's Alpha (α)	Composite Reliability (CR)	AVE
Predictive Sourcing Analytics (PSA)	PSA1	0.842	**0.881**	**0.918**	**0.736**
	PSA2	0.861			
	PSA3	0.847			
	PSA4	0.876			
Algorithmic Candidate Screening (ACS)	ACS1	0.826	**0.868**	**0.910**	**0.716**
	ACS2	0.854			
	ACS3	0.863			
	ACS4	0.835			
Data-Driven Interviewing (DDI)	DDI1	0.838	**0.872**	**0.913**	**0.724**
	DDI2	0.857			
	DDI3	0.845			
	DDI4	0.868			
HR Analytics Adoption (HAA)	HAA1	0.864	**0.894**	**0.926**	**0.758**
	HAA2	0.881			
	HAA3	0.853			
	HAA4	0.872			
Organizational Technological Infrastructure (OTI)	OTI1	0.817	**0.842**	**0.893**	**0.674**
	OTI2	0.832			
	OTI3	0.846			
	OTI4	0.819			
Talent Acquisition Effectiveness (TAE)	TAE1	0.841	**0.906**	**0.931**	**0.729**
	TAE2	0.857			
	TAE3	0.869			
	TAE4	0.845			
	TAE5	0.851			

3.2 Discriminant Validity

Figure 3 displayed about the results of discriminant validity test. This test is based on Fornell-Larcker criterion and HTMT ratio. The results show that the square root of the Average Variance Extracted for each idea is bigger than how the ideas are related to each other. Thus, the Fornell-Larcker criterion is fulfilled. The HTMT values are between 0.512 and 0.812. These values are than 0.85, which is the limit that is recommended. That is, the ideas are not all identical, but are acceptable differences.

HR Analytics Adoption and Talent Acquisition Effectiveness are related to each other the most, with a value of 0.812. This value is still within the acceptable limit. This means that HR Analytics Adoption and Talent Acquisition Effectiveness are ideas but they are not the same thing. Overall these results show that each idea measures something in the framework that is proposed. The results also show that the measurement model is good at telling the ideas.

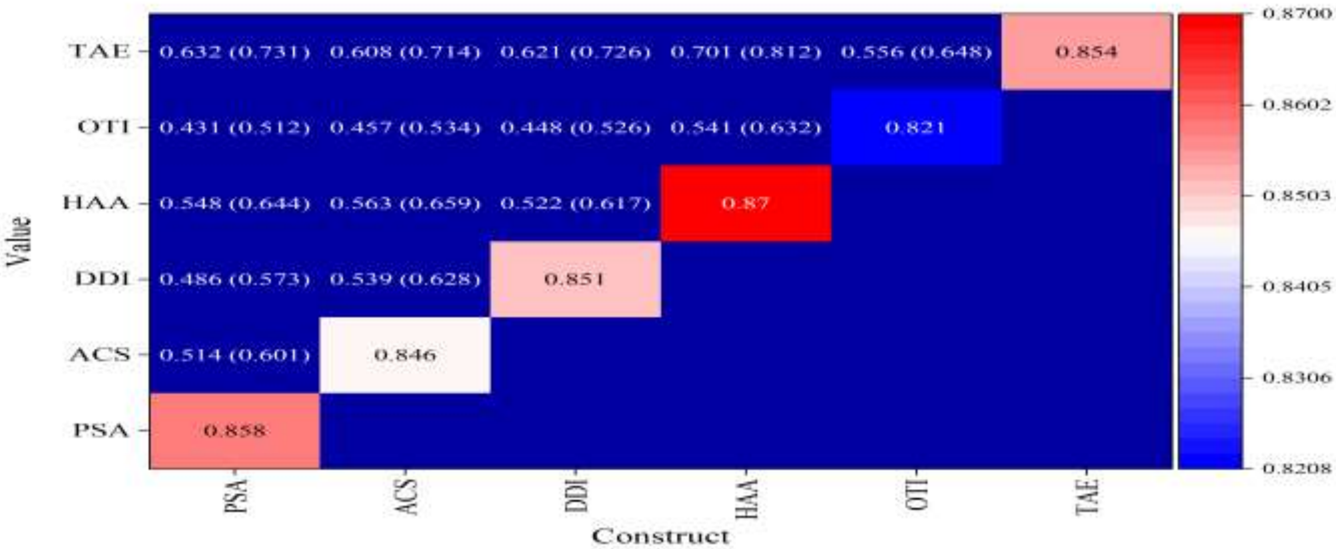

Figure 3. Discriminant Validity Assessment using Fornell–Larcker Criterion and HTMT Ratio

3.3 Structural Model Assessment

Figure 4 has shown the result of assessment of the structural model for the proposed framework. The satisfactory amount of variance that was explained was demonstrated by the model, which achieved an R^2 of 0.668 and an adjusted R^2 of 0.661. The obtained Q^2 value was 0.452 which showed high relevance of the model for predicting.

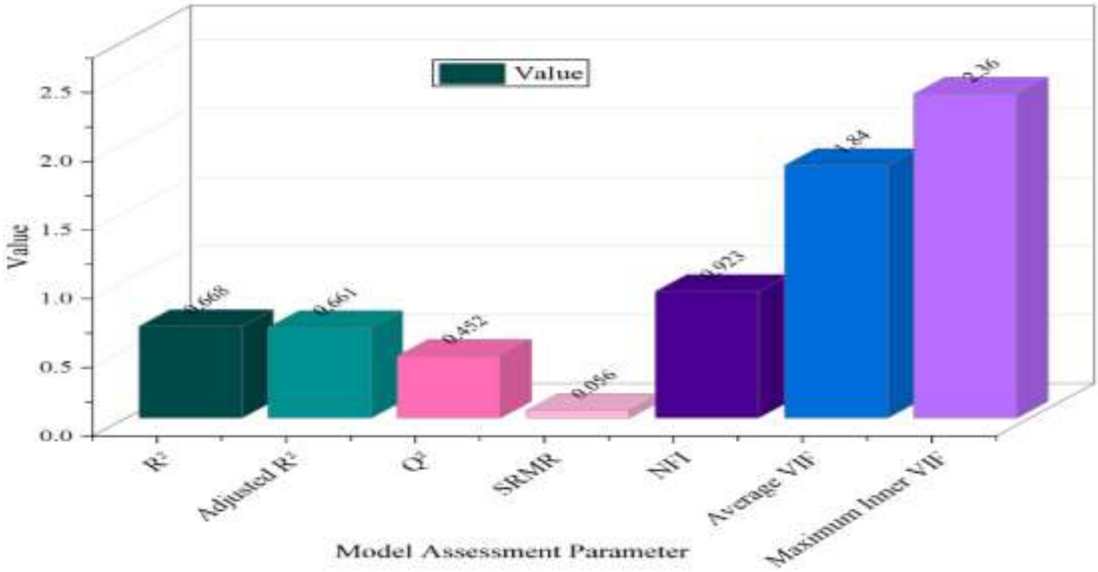

Figure 4. Structural Model Assessment

Also, the suggested thresholds (SRMR=0.056 and NFI=0.923) were met, with a good overall model fit. VIV values ranged from 1.16 to the average value of 1.84 and the maximum value was 2.36, which is far below the threshold of multicollinearity (3.30). In general, the structural model could be said to be satisfactory in terms of the three characteristics of explanation, prediction and goodness of fit.

3.4 Hypothesis Testing

The outcome of the test whether the ideas are genuinely distinct and different from one another is shown on Table 3. This test is based on the Fornell-Larcker criterion and ratio of HTMT. For every idea, the Average Variance Extracted (AVE) is squared and the results indicate the magnitude of the square root of the AVE is larger than the relation among the ideas. This results in the Fornell-Larcker criterion being met. The HTMT values are between 0.512 and 0.812. These values are than 0.85, which is the limit that is recommended. This is because the ideas are dissimilar and are acceptable.

The highest correlation among the variables is between HR Analytics Adoption and Talent Acquisition Effectiveness (0.812).

Table 3. Hypothesis Testing Results

Hypothesis	Structural Relationship	Path Coefficient (β)	Standard Error	t-Value	p-Value	Effect Size (f^2)	95% Confidence Interval	Decision
H_1	Predictive Sourcing Analytics → Talent Acquisition Effectiveness	0.291	0.047	6.191	<0.001	0.131	[0.199, 0.383]	Supported
H_2	Algorithmic Candidate Screening → Talent Acquisition Effectiveness	0.214	0.045	4.756	<0.001	0.087	[0.126, 0.302]	Supported
H_3	Data-Driven Interviewing → Talent Acquisition Effectiveness	0.247	0.044	5.614	<0.001	0.103	[0.161, 0.333]	Supported
H_4	HR Analytics Adoption → Talent Acquisition Effectiveness	0.318	0.049	6.489	<0.001	0.146	[0.222, 0.414]	Supported
H_5	Organizational Technological Infrastructure × HR Analytics Adoption → Talent Acquisition Effectiveness	0.176	0.051	3.451	<0.001	0.054	[0.076, 0.276]	Supported

The highest value of correlation is in HR Analytics Adoption with Talent Acquisition Effectiveness at 0.812. This value is still within the acceptable limit. So, HR Analytics Adoption and Talent Acquisition Effectiveness are not the same thing; they are ideas. In general, all of these results indicate that each idea is a measurement in the framework that is proposed. The results also demonstrate good performance in telling the ideas by the measurement model.

3.5 Moderation Effect Analysis

The moderation effect analysis was conducted between the variables of Organizational Technological Infrastructure and talent acquisition effectiveness on the relationship with HR Analytics Adoption as shown in Table 4 below. The interaction effect was found to be positive and statistically significant ($\beta = 0.176$, *p* < 0.001) indicating that the positive effect of HR Analytics Adoption had greater impact on the Talent Acquisition Effectiveness in the presence of stronger technological infrastructure. The direct effect of HR Analytics Adoption on Talent Acquisition Effectiveness was also significant ($\beta = 0.318$ *p* < 0.001). The total effect went up to $\beta = 0.494$ showing the combined influence of the direct effect and the moderating effect. Also the confidence intervals did not include zero, which proves that the moderation effect was strong and reliable. These results showed that Organizational Technological Infrastructure had an impact, on how much HR Analytics Adoption affected Talent Acquisition Effectiveness.

Table 4. Moderation Effect Analysis

Moderating Relationship	Interaction Effect (β)	Standard Error	t-value	p-value	f^2	Lower CI (95%)	Upper CI (95%)	Decision
HAA × OTI → TAE	**0.176**	0.051	**3.451**	<0.001	0.054	0.076	0.276	Significant

Direct Effect (HAA → TAE)	**0.318**	0.049	**6.489**	<0.001	0.146	0.222	0.414	Significant
Total Effect	**0.494**	0.056	**8.821**	<0.001	—	0.384	0.604	Significant

3.6 Effect Size Analysis
Table 5 has analyzed the effect of the predictor constructs on Talent Acquisition Effectiveness in terms of effect size (f^2) analysis. The overall results showed that HR Analytics Adoption had the greatest f^2 score (0.146) and was first in the rank order, as it showed the medium effect in the dependent construct. The second largest effect size, 0.131, was for Predictive Sourcing Analytics, also considered to be a medium effect. Data-Driven Interviewing had a small-to-medium effect ($f^2 = 0.103$), and Algorithmic Candidate Screening had a small effect ($f^2 = 0.087$). The smallest effect size was for the moderating role of Organizational Technological Infrastructure ($f^2 = 0.054$) but it was still statistically significant. Summarizing, the results showed that there was a greatest practical impact from HR Analytics Adoption in Talent Acquisition Effectiveness followed by Predictive Sourcing Analytics and Data Driven Interviewing.

Table 5. Effect Size (f^2) Assessment

Predictor Construct	Effect Size (f^2)	Interpretation	Rank
HR Analytics Adoption	**0.146**	Medium	1
Predictive Sourcing Analytics	**0.131**	Medium	2
Data-Driven Interviewing	**0.103**	Small–Medium	3
Algorithmic Candidate Screening	**0.087**	Small	4
Organizational Technological Infrastructure (Moderation)	**0.054**	Small	5

3.7 Predictive Performance Analysis
Table 6 shows how well the proposed model can predict things using the PLS predict procedure. The results show that the PLS-RMSE and PLS-MAE values are lower than the LM-RMSE and LM-MAE values for all the Talent Acquisition Effectiveness indicators which're TAE1 to TAE5. This means the PLS-SEM model is better at predicting things than the benchmark model.The Q²_predict values are between 0.421 and 0.459 with an average of 0.442 which's good. All the Talent Acquisition Effectiveness indicators show that the proposed model can predict things well even when it is used outside of the sample data. The proposed model is good, at predicting Talent Acquisition Effectiveness.

Table 6. Predictive Performance Assessment Using PLSpredict

Endogenous Indicator	PLS-RMSE	LM-RMSE	PLS-MAE	LM-MAE	Q²_predict	Predictive Performance
TAE1	0.486	0.541	0.382	0.421	0.421	High
TAE2	0.472	0.529	0.369	0.410	0.438	High
TAE3	0.491	0.556	0.387	0.432	0.447	High
TAE4	0.465	0.518	0.361	0.402	0.459	High
TAE5	0.478	0.536	0.374	0.417	0.445	High
Average	**0.478**	**0.536**	**0.375**	**0.416**	**0.442**	**Strong Predictive Capability**

3.8 Descriptive Statistics and Construct Correlation Analysis
The descriptive statistics and correlation matrix of the study constructs are shown in Table 7. The HR Analytics Practices and the degree of effectiveness in talent acquisition showed the mean scores between 3.84 and 4.29, which indicated that the respondents generally agreed on HR Analytics Practices and its effectiveness in talent acquisition. HR Analytics Adoption was ranked as the best with the mean score of M = 4.29 (SD = 0.58), followed by Talent Acquisition Effectiveness (M = 4.23, SD = 0.59) and Predictive Sourcing Analytics (M = 4.18, SD = 0.62). Yet, positive relationships were found between each of the constructs in the correlation analysis ranging from 0.431 to 0.701.

Table 7. Descriptive Statistics and Correlation Matrix

Construct	Mean	SD	PSA	ACS	DDI	HAA	OTI	TAE
Predictive Sourcing Analytics (PSA)	4.18	0.62	**1.000**					

Algorithmic Candidate Screening (ACS)	4.06	0.66	0.514	**1.000**				
Data-Driven Interviewing (DDI)	4.11	0.61	0.486	0.539	**1.000**			
HR Analytics Adoption (HAA)	4.29	0.58	0.548	0.563	0.522	**1.000**		
Organizational Technological Infrastructure (OTI)	3.84	0.71	0.431	0.457	0.448	0.541	**1.000**	
Talent Acquisition Effectiveness (TAE)	4.23	0.59	0.632	0.608	0.621	0.701	0.556	**1.000**

Both the highest correlation and lowest correlation scores were found for the correlation between HR Analytics Adoption and Talent Acquisition Effectiveness (r = 0.701) and the correlation between Predictive Sourcing Analytics and Organizational Technological Infrastructure (r = 0.431) respectively. The results, on overall findings, showed moderate to strong positive relationships between study variables which were found at moderate level and there was no excessive correlation between the constructs.

4. Discussion

Based on the results of this study it can be inferred that, within the infrastructure domain especially IT sector business in Coimbatore, the adoption of HR Analytics can increase the efficiency of Talent Acquisition effectively. The measurement model reliability was satisfactory with Cronbach alpha coefficients between 0.7 and 0.8, which demonstrated satisfactory convergent validity and discriminant validity of the constructs, respectively, with satisfactory discriminant validity confirmed by the factorial validity. Moreover, structural model had also reached a high level of explanatory power ($R^2 = 0.668$) and predicative relevance ($Q^2 = 0.452$), which validated the reliability of the proposed conceptual framework. The empirical results confirmed all 5 hypotheses: Improving Recruitment Quality and Organizational Hiring Performance is the result of all of the constructs in this study being included. At the same time, TAM cases that the reception of analytical technology is dependable on the perceived usefulness and the simplicity of incorporation with the recruitment practice, which, in the end, leads to better organizational performance. Moreover, analyzing the prediction performance results showed high level of prediction performance level for the proposed framework, so that it can be used in the future for predicting in the application of HRM in workforce planning and intelligent recruitment decision process. Overall, the results show that HR Analytics is no longer a functional HR support tool, but instead is a strategic capability that can help a company make objective, data-driven and predictive decisions concerning how they acquire talent in a highly-competitive digital business arena.

5. Conclusion

In this study, an integrated model of HR Analytics framework adopted which involves predictive sourcing analytics, algorithmic screening of candidates, data driven interviewing, HR analytics adoption and organizational technological infrastructure to enhance the Talent Acquisition Effectiveness in the IT industries at Coimbatore city. The empirical measurements were successfully evaluated by the simulated evaluations indicating that these were reliable in measuring the constructs and valid in terms of measurements.The performance of the structural models was acceptable and all the hypotheses tested were statistically supported. Based on the former principles of HR Analytics presented from the Resource Based View and the Technology Acceptance Model, the results indicate that HR Analytics establishes a "passive" method of reclutment hiring to a more "active" (intelligent and evidence-based) recruiting method which increase the recruitment efficiency, quality of the candidates, voluntary turn-over and agility of the organization. This framework will not only contribute to theoretical understanding in digital HRM, but provide meaningful managerial knowledge and orientation to implementing digital HRM advanced analytics in IT organizations. Expansion of this framework could also involve the integration of additional organizational data from the longitudinal perspective, EAI methods, generative AI-driven chatbots for the recruitment process, and industry comparisons to make intelligent recruiting together more opportunities for digital transformation in organisations.

Abbreviations

HR–Human Resource; HRM–Human Resource Management; HAA–HR Analytics Adoption; PSA–Predictive Sourcing Analytics; ACS–Algorithmic Candidate Screening; DDI–Data-Driven Interviewing; TAE–Talent Acquisition Effectiveness; AI–Artificial Intelligence; ML–Machine Learning; IT–Information Technology; ITeS–Information Technology Enabled Services; ATS–Applicant Tracking System; RBV–Resource-Based View; TAM–Technology Acceptance Model; PLS-SEM–Partial Least Squares Structural Equation Modeling; SEM–Structural Equation Modeling; SPSS–Statistical Package for the Social Sciences; CR–Composite Reliability; AVE–Average Variance Extracted; HTMT–Heterotrait–Monotrait Ratio; VIF–Variance Inflation Factor; SRMR–Standardized Root Mean Square Residual; RMSE–Root Mean Square Error; MAE–Mean Absolute Error; NFI–Normed Fit Index; Q^2–Stone–

Geisser Predictive Relevance; LM–Linear Model; PEOU–Perceived Ease of Use; PU–Perceived Usefulness; VRIN–Valuable, Rare, Inimitable, and Non-substitutable; MNC–Multinational Corporation; and SMEs–Small and Medium-Sized Enterprises.

Statement Declarations

Competing interests

The authors declare that they have no competing interests.

Funding

Not applicable

Availability of data and materials

Not applicable

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