Empirical Analysis of AI Adoption for Talent Acquisition: A Study on Technological, Organisational and Demographic Determinants

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ABSTRACT

Integrating Artificial Intelligence (AI) in talent acquisition is changing recruitment processes, yet the factors influencing its adoption remain underexplored. The main factors affecting the usage of AI technologies in talent acquisition across various organizations are examined in this study. Utilizing the TOE model and Demographic characteristics, the research examined variables such as complexity, compatibility, competition, management support, relative advantages, and security & privacy concerns. Data was collected through a questionnaire and online survey from 240 employees working in IT companies based in Delhi-NCR. Findings revealed that compatibility, competition, relative advantages, and security issues significantly influenced AI adoption. Additionally, demographic variables such as income, professional experience, age, and education moderated these relationships. The results provide actionable insights that HR managers, AI developers, and organizational leaders can use to enhance the effective implementation of AI in recruitment. The study adds to the literature by offering a framework that bridges theoretical concepts with practical applications, guiding organizations in leveraging AI to optimize their hiring strategies.

Keywords: Artificial Intelligence, Demographic Factors, Recruitment, Talent Acquisition, Technology Adoption

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INTRODUCTION

Human skill is what will ensure the creation of original ideas, the seamless implementation of plans, and the monitoring of organizational performance spikes. Technology is the collection of tools that make process optimization easier. There is hence a justifiable interest in finding out more about the interaction between this technology and human resources (Jatobá et al., 2019). A business's ability to attract, recognize, and retain excellent workers has a direct bearing on its ability to innovate, grow, and maintain a competitive edge. Nevertheless, traditional methods of identifying talent often proved to be biased and resource- and labor-intensive (O'Shea & Puente, 2018).

Artificial intelligence (AI) is the capacity of machines to demonstrate intelligence (Ahmed, 2018). The term AI includes a wide classification of technologies that enable humans to execute activities that they are capable of performing, including human intelligence, pattern recognition, decision-making analytics, spoken and visual recognition, and language translation utilizing a specialized algorithm (Nawaz, 2019). These days, machines that can understand spoken language, play strategic games like Go and chess at the highest level, drive themselves, and employ intelligent routing in content delivery networks and war simulations are all commonly referred to as artificial intelligence (Ahmed, 2018). Artificial intelligence is the subfield of computer science that solves problems more quickly by using logical reasoning, rapid thinking with a wealth of knowledge, and human-like thinking (R & Bhanu Sree, 2018). In 1956, John McCarthy gave the phrase "artificial intelligence." During a scholarly conference, he provided a definition of the word and said that applied science, biology, psychology, medical sciences, and interdisciplinary studies will eventually benefit from AI (Nawaz & Gomes, 2019).

Since it's still unknown what will drive AI adoption in recruitment, most of the applications of AI for hiring talent are in the initial stage and have not been deployed in the commercial sector (Lengnick-Hall, Neely, & Stone, 2018). Research on HR managers' adoption of AI for talent acquisition is crucial since it will give them more knowledge on how to use AI for training and development. Performance of the HR function and personnel department will be increased with the use of AI (Upadhyay & Khandelwal, 2018). By automating the repetitive tasks and efficiently processing the large volumes of data, AI improves recruitment efficiency which is critical for large scale organizations to stay up with technological advancements (Lodra, Padhana, & Kristin, 2024). Despite the fact that AI has several advantages for recruiters, HR managers in businesses are not using AI technology as much for talent acquisition (Albert, 2019). This innovative study examined the factors and use of AI for TA in organizations empirically and goes on to evaluate the effect of demographic elements on the usage of AI.

The following were the research questions:

1. What are the factors affecting the usage of artificial intelligence for TA?
2. Is usage of artificial intelligence for TA affected by the demographic factors?

AI marketers, developers, and HR managers will find this research useful in understanding how AI is actually being adopted and used for hiring talent. It will help companies create AI-driven TA technologies.

This paper will examine the theoretical foundation after the introduction and then the literature review on AI technologies and their adoption for talent acquisition to address the questions of research. A conceptual framework diagram depicting the relationship between elements affecting the usage of AI for talent acquisition is then presented. Based on the literature review, hypotheses are developed in the next section, and then tested to check the relationship between variables. The results and discussion aim to shed light on relationships between various elements affecting the adoption of AI. At the end, the conclusion is given with the practical implications of the study.

Theoretical Background

Several technology acceptance models were used in earlier studies, which examined the adoption of technology at the individual level (Singh, 2018). These models- ‘Theory of Reasoned Action (TRA)’, ‘Theory of Planned Behavior (TPB)’ (Ajzen, 1991), ‘Technology Acceptance Model (TAM)’ (Davis, 1989), and ‘Unified Theory of Acceptance (UTAUT)’ (Venkatesh, Morris, Davis, & Davis, 2003)-were mostly centered on technology, and explained from an individual viewpoint. The TOE Model (Wiarda, Depietro, & Fleischer, 1990), which has greater explanatory power, addresses technology adoption from an organizational standpoint. This model's capacity for explanation has been shown in a variety of national, industrial, and technological situations (Hsu, Kraemer, & Dunkle, 2006).

Model's 'T' perspective considers the technological resources, both internal and external, that an organization needs to adopt technology (Khemthong & Roberts, 2014). The technology factors, which were discussed, are technological benefits, IT solution compatibility, relative advantage cost, capacity, and reliability (Park & Kim, 2019). The 'O' perspective places emphasis on factors like the magnitude of the firm and its size, the organization's structural formalization, system's intricacy, caliber of human elements, support from upper management, and organization preparedness (Baig, Shuib, & Yadegaridehkordi, 2019). From an 'E' standpoint, an organization's competitors, industry and vendor support, and laws and regulations are taken into account (Daradkeh, 2019). Numerous studies that used the TOE Framework looked at the variables that positively affected AI adoption (Chau & Tam, 1997). At the moment, certain studies looked at AI applications in particular fields (Kushwaha, et al., 2020). Additional research studies examined the theoretical underpinnings of AI (Murphy, 2018). Studies on adoption of AI, especially at the organizational level, are scarce.

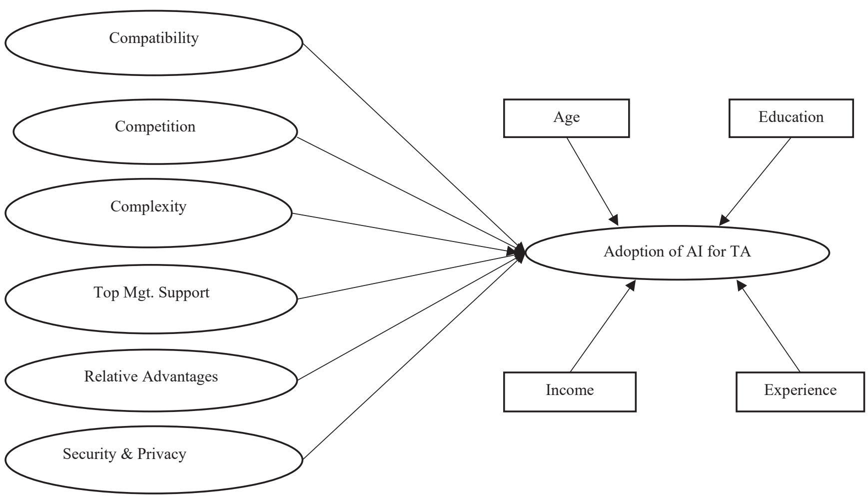

Figure 1: Conceptual Framework
Source: Self-complied by the authors

According to the evaluation of research on AI acceptance, a good place to start looking into AI adoption is with the TOE framework (Oliveira & Martins, 2011). This study was also extended to include demographic factors to check AI adoption.

REVIEW OF LITERATURE AND HYPOTHESIS DEVELOPMENT

The usage of AI technology is a significant subject of research, being done in many different settings all around the world. Research has been carried out on adopting of AI-based technologies- AI and Machine Learning in Finance (Goodell, Kumar, & Lim, 2021), AI in Human Computer Gaming (Yin, Yang, Huang, & Wang, 2023), Artificial Intelligence and Robotics (Brady, 1984), Adoption of it in Urban areas (Herath & Mittal , 2022) and Role of AI in Recruitment (Al-Alawi, Naureen, & Al-Alawi, 2021). Artificial intelligence might be able to recognize speech, make decisions, and perceive images. Algorithms and machine learning tools possess the capacity to quickly handle vast volumes of data, find recurring themes and patterns, and optimize, and predict tendencies (Chen, 2022). AI-based technologies are now assisting HR in automating a substantial portion of repetitive operations in hiring procedures such as searching the potential candidates, selecting them, engaging and re-engaging them, building relations, onboarding, and many other activities that used to take a lot of time in the past (Takhi, Gosain, & Singh, 2020). Based on the literature, hypotheses were developed in the study.

Hypothesis Development

Compatibility

Compatibility may be characterized as "the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters" (Rogers, 2003). Compatibility in this context refers to how much innovation and technology can satisfy the needs of potential adopters while also offering value and experience (Chong & Olesen, 2017). Prior research suggests that compatibility benefits AI specifically as well as the adoption of IT in general (Verma & Chaurasia, 2019). If AI technology were integrated with the current IT setup, the estimated time and cost of its implementation would be minimized. Therefore, the need arises to check the relationship between these two:

H1: Compatibility of Technology influences the adoption of AI for Talent Acquisition.

Competition

Pressure a business feels from its rival firms is referred to as competition (Oliveira & Martins, 2010). This pressure is having a big impact on how decisions are made in contemporary businesses and is a major indicator of the adoption of IT innovations. Based on empirical research, the usage of IT advances is significantly influenced by severe competition and competitive pressure (Low, Chen, & Wu, 2011). HR managers must constantly monitor the TA technology being utilized by their competitors, as well as any new TA procedures they may have established. Frequently, implementing new techniques is a tactical necessity to remain competitive in the job market (Sumner, 2000). Therefore, it is necessary to evaluate the relationship given below:

H2: Competition influences the adoption of AI for Talent Acquisition.

Complexity

It describes the degree to which technology is deemed comparatively hard to use and comprehend. Based on the studies that have been published, the AI technology usage rate may rise if its complexity were reduced (Lu, Luo, Wang, & Le, 2015). The degree of complexity reflects how challenging employers perceive AI recruiting tools to be to utilize. Comparing AI to traditional IT, it is a distinguishing high-tech feature that is more challenging to implement and requires a substantial amount of IT knowledge to grasp, many firms may find that the technological novelty of AI recruitment tools makes them complex (Pan et al., 2021). Therefore, the relationship between complexity and the adoption of AI is tested by this hypothesis:

H3: Complexity influences the adoption of AI for Talent Acquisition.

Top Management Support

The literature discusses how managerial support affects views towards the deployment of AI significantly (Awiagah, Kang, & Lim, 2015).

Furthermore, management backing is necessary to advance the adoption of technologies that bring about significant alterations for ultimate users (Obal & Morgan, 2018). This support is also required for the adoption of new tools and techniques since they actively and openly support their implementation (Chong & Chan, 2012). Senior management should be convinced to support AI for talent acquisition since they supply the necessary supplies for this novel technology (Alam, Masum, Beh, & Hong, 2016). So the need arises to check the relationship between these two:

H4: Top Management Support influences the adoption of AI for Talent Acquisition.

Relative Advantages

It often describes the extent to which innovations can benefit a company (Kraemer, Zhu, Xin Xu, & Dong, 2006). If revolutionary technology is seen to offer relative advantages over the organization's present technology or procedures, there is a greater chance that it will be adopted (Lee, Miranda, & Kim, 2004). Recruiters can search and select people more easily than using conventional recruitment methods thanks to AI technology (Albert, 2019). HR managers are benefiting from AI tools for TA in terms of improved recruitment outcomes (Upadhyay & Khandelwal, 2018) which makes one want to find out more about the association between relative advantages and usage of AI for talent acquisition.

H5: Relative Advantages influence the adoption of AI for Talent Acquisition.

Security & Privacy

Data privacy becomes critical when AI systems significantly rely on large datasets, many of which contain sensitive personal information (Shafee & Awaad, 2021). Security and privacy stand for the degree of supposed insecurity of the technology and information system for carrying out tasks and exchanging data (Zhu, Dong, Xin Xu, & Kraemer, 2006). Privacy concerns are brought up by the use of AI in talent acquisition, particularly when algorithms are used to go through massive amounts of data to find suitable applicants. To keep people's trust both present and potential one must guarantee the confidentiality and integrity of this data (Verma & Chaurasia, 2019). So the need arises to check the relationship between these two:

H6: Security & Privacy influence the adoption of AI for Talent Acquisition.

Demographic Characteristics

Marital status, gender, age, job experience years, educational achievement, and position are used to characterize demographic traits. In the present study age, education, income, and experience are used to understand the usage of AI for talent acquisition with regard to demographic variables. Age can affect the usage of AI for talent acquisition, as different generations have varying levels of technological familiarity, comfort with digital tools, and adaptability to change (Wilson & Daugherty, 2018). Studies have shown that older workers often prefer traditional methods of recruitment, relying more on human intuition and judgment, and may view AI as less reliable or even as a potential threat to job security in recruitment roles (Fountaine, McCarthy, & Saleh, 2019). Studies show that individuals with advanced education, especially in fields related to technology and business, are more likely to recognize the benefits of AI in improving efficiency, reducing bias, and enhancing decision-making in hiring processes (Frank, et al., 2019). Higher-income organizations can also invest in training their staff to effectively use AI, which facilitates smoother adoption and integration into their talent acquisition processes (Brynjolfsson & McAfee, 2017). On the other hand, smaller or lower-income companies may lack the resources or expertise to experiment with and adopt new technologies (Bughin, Seong, Manyika, Chui, & Joshi, 2018). Experience with evolving technologies can make individuals more adaptable to AI innovations, as they understand the benefits of automation in streamlining complex tasks (Devenport & Ronanki, 2018). Therefore, the effect of these demographic factors is assessed through these hypotheses:

H7: There is no significant difference in the adoption of AI for talent acquisition based on age.

H8: There is no significant difference in the adoption of AI for talent acquisition based on education.

H9: There is no significant difference in the adoption of AI for talent acquisition based on income.

H10: There is no significant difference in the adoption of AI for talent acquisition based on experience.

RESEARCH METHODOLOGY

Research Survey Instrument Design

For creating the measurement scale, the body of existing TOE literature was taken into account. Six specialists in TA function from the IT sector evaluated the survey questionnaire before the data collection. Prior to the questionnaire assessment, these experts were completely conscious of the purpose and extent of the study. A five-point Likert scale with options from strongly disagree to strongly agree was used to measure the components in this questionnaire, which was employed for the pilot study. For the pre-test (which had 50 respondents), the data's internal consistency and reliability were assessed using Cronbach's alpha. A pilot test was done with 100 respondents. This study took into account the TA and HR managers who work for IT companies that use AI technology for TA as respondents.

Sampling and Data Collection

Primary data was collected from the respondents using the structured questionnaire. The intended responders were TA and HR managers from Delhi-NCR area IT enterprises located in different software technology parks and IT hubs. The researchers made certain that these participants were utilizing AI technologies and strategies for technical assistance. Researchers employed the convenience sampling technique to gather primary data from over 240 IT workers in the Delhi-NCR area. Data was gathered online using Google Forms between October 2023 and June 2024. Questionnaire links were communicated via social media sites like LinkedIn and Twitter and personal connections. Only 240 of the total responses were accurately and completed fully, making them eligible for further analysis. IBM SPSS version 21 and Smart PLS version 4 were utilized for the analytical portion.

DATA ANALYSIS AND RESULTS

There are two sections in the data analysis. In the first section, using the SPSS program, a descriptive analysis was performed on the respondents' demographic features; Table 1 displays the findings. Data analysis for this study in this section is done using SmartPLS version 4. With regard to the second section of the analysis, the effect of demographic factors on adopting AI for acquiring talent was assessed by using the One-way ANOVA technique for which the SPSS software was used.

Demographic Characteristics

Table 1 displays the outcomes derived from demographic attributes. Regarding age, the majority of those surveyed (45.8%) were within 31-40 years age group. Respondents followed this age group between the <30 years group (35.8%), 41-50 group (13.8%), and 51-60 group (4.6%). In terms of gender categories, the findings showed that men (58%) predominated in the sample as opposed to women (42%). Respondents with a master's degree (41.7%) and graduation degrees (29.2%) predominated a doctorate (18.3%) and any other professional certificate (10.8%). Regarding income, most of the respondents were between the group 10-20 lakhs (35.8%) followed by the 20-30 lakhs group (26.3%). Respondents having experience between 10-15 years were the most (44.6%) and less than 5 years and more than 15 years were 12.9%.

Table 1: Demographic Profile

Gender	Frequency	Percent	Age		
Male	140	58.0	<30 years	86	35.8
Female	100	42.0	31-40 years	110	45.8
Total	**240**	**100.0**	41-50 years	33	13.8
			51-60 years	11	4.6
			Total	**240**	**100.0**
Education			**Income**		
Graduate	70	29.2	<10 lakhs	49	20.4
Post graduate	100	41.7	10-20 lakhs	86	35.8
Doctorate	44	18.3	20-30 lakhs	63	26.3
Any other	26	10.8	>30 lakhs	42	17.5
Total	**240**	**100.0**	**Total**	**240**	**100.0**
Experience					
<5 years	31	12.9			
5-10 years	71	29.6			
10-15 years	107	44.6			
>15 years	31	12.9			
Total	**240**	**100.0**			

Source: Self-compiled by the authors using primary data analysis

Measurement Model

The measurement model analysis was conducted by using three primary criteria: convergent validity, factor loadings, and discriminant validity. All of the indicators received scores higher than 0.70, for factor loadings, indicating a satisfactory fit for the measurement model. Convergent validity was attained when a construct's AVE was more than 0.50. All constructs had a value of more than 0.50, as shown in Table 2, indicating strong convergent validity.

Table 2: Factor Loadings and Quality Criteria (Composite Reliability, AVE, Cronbach's Alpha)

Constructs	Items	Loadings	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	AVE
Adoption of AI (AA)	AA1	0.911	0.94	0.94	0.954	0.806
	AA2	0.89				
	AA3	0.888				
	AA4	0.891				
	AA5	0.909				
Compatibility (Cmpt)	Cmpt1	0.902	0.912	0.914	0.945	0.85
	Cmpt2	0.933				
	Cmpt3	0.932				
Competition (Comptn)	Comptn1	0.862	0.854	0.861	0.911	0.773
	Comptn2	0.891				
	Comptn3	0.884				
Complexity (Cmply)	Cmply1	0.924	0.802	0.813	0.886	0.724
	Cmply2	0.897				
	Cmply3	0.717				
Top Management Support (MS)	MS1	0.884	0.846	0.858	0.906	0.763
	MS2	0.887				
	MS3	0.849				

Relative Advantages(RA)	RA1	0.942	0.925	0.928	0.953	0.87
	RA2	0.94				
	RA3	0.915				
Security & Privacy (S&P)	S&P1	0.929	0.929	0.932	0.955	0.876
	S&P2	0.926				
	S&P3	0.953				

Source: Self-compiled by the authors using primary data analysis

The study used Fornell and Larcker and HTMT as its two criteria to check for discriminant validity. According to Fornell and Larcker criteria, as can be observed in Table 3, the values fell between 0.851 and 0.936 according to the square root of the AVE. Since these values exceeded the bivariate correlation between any two-research constructs, we claimed discriminant validity.

Table 3: Discriminant Validity- Fornell and Larcker Criterion

	Adoption of AI	Compatibility	Competition	Complexity	Management Support	Relative Advantage	Security & Privacy
Adoption of AI	0.898						
Compatibility	0.63	0.922					
Competition	0.749	0.613	0.879				
Complexity	0.644	0.897	0.749	0.851			
Management Support	0.724	0.616	0.899	0.735	0.874		
Relative Advantage	0.79	0.636	0.834	0.671	0.823	0.933	
Security & Privacy	0.775	0.575	0.718	0.609	0.723	0.791	0.936

Source: Self-compiled by the authors using primary data analysis

To ascertain whether discriminant validity was present, the HTMT values needed to be less than 0.85. The HTMT values in this study, which ranged from 0.623 to 0.846 as in Table 4, supported the presence of discriminant validity between the model's constructs.

Table 4: Discriminant Validity- HTMT Criterion

	Adoption of AI	Compatibility	Competition	Complexity	Management Support	Relative Advantage
Adoption of AI						
Compatibility	0.678					
Competition	0.827	0.688				
Complexity	0.743	0.639	0.819			
Management Support	0.796	0.689	0.751	0.837		
Relative Advantage	0.846	0.691	0.726	0.784	0.809	
Security & Privacy	0.827	0.623	0.795	0.709	0.8	0.843

Source: Self-compiled by the authors using primary data analysis

Structural Model

Table 5 shows the hypothesis results. At the 5% significance threshold, competition, relative advantages, compatibility, and security and privacy issues were all less than 0.05. Thus, hypotheses H1, H2, H5, and H6 were backed by the conclusions of the research. For complexity and management support, p values were more than 0.05, and thus the hypotheses H3: Complexity influences the adoption of AI for Talent Acquisition and H4: Management Support influences the adoption of AI for Talent Acquisition were not backed by the results.

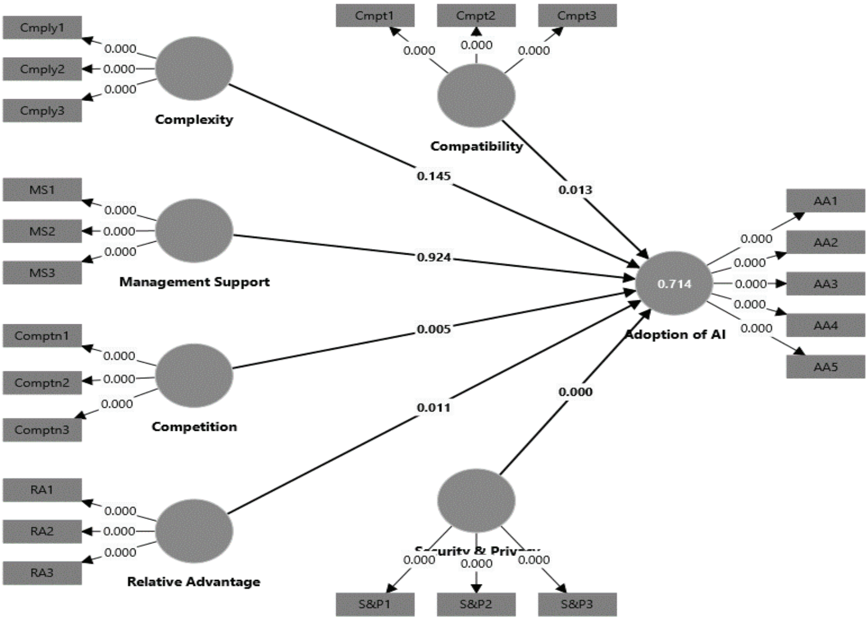

Figure 2: Structural Model's Results

Source: Self-compiled by the authors using primary data analysis

Table 5: Findings from Hypotheses Testing

	Original Sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Interpretation
Compatibility -> Adoption of AI	0.249	0.239	0.1	2.495	0.013	Accepted
Competition -> Adoption of AI	0.256	0.253	0.092	2.785	0.005	Accepted
Complexity -> Adoption of AI	-0.14	-0.129	0.096	1.459	0.145	Rejected
Management Support -> Adoption of AI	-0.009	-0.01	0.091	0.095	0.924	Rejected
Relative Advantages -> Adoption of AI	0.248	0.253	0.098	2.531	0.011	Accepted
Security & Privacy -> Adoption of AI	0.344	0.342	0.084	4.085	0.000	Accepted

Source: Self-compiled by the authors using primary data analysis

Analyzing the Adoption of AI for Talent Acquisition for Demographic Characteristics

In this section, the second objective of this study was to examine the differences in the adoption of AI for talent acquisition by demographic characteristics. While gaining an insight into the differences in the adoption of AI, hypotheses from H7-H10 were framed and tested by employing statistics, namely, One-Way ANOVA.

Table 6: ANOVA-Age

		Age				
		Sum of Squares	**Df**	**Mean Square**	**F**	**Sig.**
AA1	Between Groups	6.156	3	2.052	1.553	.201
	Within Groups	311.777	236	1.321		
	Total	317.933	239			
AA2	Between Groups	6.042	3	2.014	1.752	.157
	Within Groups	271.254	236	1.149		
	Total	277.296	239			
AA3	Between Groups	5.290	3	1.763	1.331	.265
	Within Groups	312.644	236	1.325		
	Total	317.933	239			
AA4	Between Groups	3.946	3	1.315	1.210	.307
	Within Groups	256.550	236	1.087		
	Total	260.496	239			
AA5	Between Groups	4.900	3	1.633	1.234	.298
	Within Groups	312.284	236	1.323		
	Total	317.183	239			

Source: Self-compiled by the authors using primary data analysis

With p-values for all AA1, AA2, AA3, AA4, and AA5 being more than 0.05, as shown in Table 6 it was clear that there was no significant difference in the use of AI for talent acquisition depending on age. So the hypothesis H7 was accepted.

Table 7: ANOVA-Education

Education						
		Sum of Squares	df	Mean Square	F	Sig.
AA1	Between Groups	5.907	3	1.969	1.489	.218
	Within Groups	312.026	236	1.322		
	Total	317.933	239			
AA2	Between Groups	1.490	3	.497	.425	.735
	Within Groups	275.806	236	1.169		
	Total	277.296	239			
AA3	Between Groups	3.525	3	1.175	.882	.451
	Within Groups	314.408	236	1.332		
	Total	317.933	239			
AA4	Between Groups	9.813	3	3.271	3.079	.028
	Within Groups	250.683	236	1.062		
	Total	260.496	239			
AA5	Between Groups	13.745	3	4.582	3.563	.015
	Within Groups	303.439	236	1.286		
	Total	317.183	239			

Source: Self-compiled by the authors using primary data analysis

With p-values for all AA1, AA2, AA3, AA4, and AA5 being more than 0.05, as shown in Table 7 it was clear that the use of AI for talent acquisition based on education did not differ much from one another. So the hypothesis H8 was accepted.

Table 8: ANOVA-Income

Income						
		Sum of Squares	df	Mean Square	F	Sig.
AA1	Between Groups	5.161	3	1.720	1.298	.276
	Within Groups	312.772	236	1.325		
	Total	317.933	239			
AA2	Between Groups	5.518	3	1.839	1.597	.191
	Within Groups	271.778	236	1.152		
	Total	277.296	239			
AA3	Between Groups	3.087	3	1.029	.771	.511
	Within Groups	314.847	236	1.334		
	Total	317.933	239			

AA4	Between Groups	4.184	3	1.395	1.284	.281
	Within Groups	256.312	236	1.086		
	Total	260.496	239			
AA5	Between Groups	5.541	3	1.847	1.399	.244
	Within Groups	311.642	236	1.321		
	Total	317.183	239			

Source: Self-compiled by the authors using primary data analysis

With p-values for all AA1, AA2, AA3, AA4, and AA5 being more than 0.05, as shown in Table 8 it was clear that the use of AI for talent acquisition based on income did not differ much from one another. So the hypothesis H9 was accepted.

Table 9: ANOVA-Experience

Experience						
		Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
AA1	Between Groups	3.937	3	1.312	.986	.400
	Within Groups	313.996	236	1.330		
	Total	317.933	239			
AA2	Between Groups	7.914	3	2.638	2.311	.077
	Within Groups	269.381	236	1.141		
	Total	277.296	239			
AA3	Between Groups	4.595	3	1.532	1.153	.328
	Within Groups	313.339	236	1.328		
	Total	317.933	239			
AA4	Between Groups	3.106	3	1.035	.949	.417
	Within Groups	257.390	236	1.091		
	Total	260.496	239			
AA5	Between Groups	7.808	3	2.603	1.985	.117
	Within Groups	309.375	236	1.311		
	Total	317.183	239			

Source: Self-compiled by the authors using primary data analysis

With p-values for all AA1, AA2, AA3, AA4, and AA5 being more than 0.05, as shown in Table 9 it was clear that the use of AI for talent acquisition based on experience did not differ much from one another. So the hypothesis H10was accepted.

DISCUSSION

In this study, we explored and analyzed the factors affecting the adoption of AI for talent acquisition in the IT companies in the Delhi-NCR region. Given that AI is recognized as a critical innovation for almost all sectors, especially in developing countries, it is essential to understand the factors that are affecting the usage of this technology. To address the gaps, this study combined the TOE (Technology, Organization, and Environment) framework with the demographic characteristics of the respondents. A conceptual framework was developed that reflected the study's proposed relationships. The investigated adoption predictors were classified into two main constructs. The first construct was TOE represented by six variables compatibility, complexity, management support, relative advantages, competitive pressure, and security & privacy concerns. The second construct was demographic characteristics like age, income, education, and experience of the respondents, which affected the adoption of AI for talent acquisition.

The results showed that the Compatibility of Technology influenced the adoption of AI for Talent Acquisition (Rogers, 2003). Hence, in this work, H1 was supported as the anticipated cost and time associated with implementing AI technology will be reduced if it is compatible with current IT settings. AI can therefore be embraced more readily. Compatibility signified the degree to which AI recruitment applications were perceived as harmonious with the current policies, values, and practices of the organization, and HRM.

Competition influenced the adoption of AI (Alam, Masum, Beh, & Hong, 2016) for talent acquisition, which showed that H2 was confirmed. Organizations are facing pressure to adopt AI for TA, as it enhances the TA function across the industry (Kin Tong & Sivanand, 2005). Therefore, organizations need to adopt AI for TA due to competitive pressure.

Prior research has indicated that the degree of IT maturity had a major impact on how strategically businesses choose to acquire and use IT. Contrary to the prior results (Al-Dmour, Love, & Al-Debei, 2016), (Oliveira, Thomas, & Espadanal, 2014) the findings of the study (Urus, Rahmat, Othman, & Rasit, 2024) showed that the complexity of the technology was not significant for big data analytics deployment which was in line with our empirical results that complexity was not a significant predictor for the adoption of AI for talent acquisition and H3 was not supported.

Any new technology system requires support from the top management when it needs to be adopted and implemented (Alam, Masum, Beh, & Hong, 2016), (Pillai et al., 2022). On the contrary, in terms of the relationship between top management support and the adoption of AI for talent acquisition, our finding is consistent with a prior study (Marler & Parry, 2016) which showed that the decentralized nature of digital tools allows HR professionals to experiment with and implement AI solutions without extensive top-down involvement. A survey by the Society for Human Resource Management (SHRM) found that over 90% of HR leaders actively involved in the adoption of AI tools, with many making decisions independently of senior leadership direction (Popera, 2024).

Consistent with the prior studies (Pillai et al., 2022), (Alam, Masum, Beh, & Hong, 2016) our study also revealed that relative advantages and security & privacy had a positive influence on the adoption of AI for talent acquisition. Hence, H5 and H6were supported. HR managers can find and hire people more quickly than using conventional recruitment methods. TA managers are concerned about the personal data of the candidates transmitted through AI for TA and feel insecure, as this data is highly confidential. The privacy of this candidate's data is vital therefore; HR managers have a concern about the security and privacy of data passing through AI for TA.

In regard to demographic characteristics of the respondents, the impact of age, education, income, and experience on the adoption of AI for talent acquisition was explored. Age differences may be a determining factor in how well people do their jobs and are ready to adopt the new technology (Smedley & Whitten, 2008). An individual employee's degree of education is also a crucial component that may affect the adoption of technology in the workplace and improve an employee's success in the selected work environment (Hunter, 1986). Educational accomplishment refers to an individual's academic qualifications or degrees. Job experience accumulates relevant information, skills, and abilities. Income increases with experience so both the factors income and experience are considered for the adoption of technology. Employees invest their experience in themselves, which improves their ability to adopt the technology (Ng & Feldman, 2013).

Results of the study showed that these demographic characteristics did not influence the adoption of AI for talent acquisition. There was no significant difference between the adoption of AI for talent acquisition based on age, education, income, and experience. Hence, H7, H8, H9 and H10 were accepted. The adoption of AI for talent acquisition was not significantly influenced by factors like age, education, income, or experience because modern AI tools are designed to be accessible and user-friendly. These platforms are often intuitive, requiring minimal technical expertise, making them easy to adopt across different user demographics. As AI tools are increasingly integrated into HR processes, companies provide training and support to employees, ensuring that individuals, regardless of their background, can adapt and use the technology effectively. Additionally, AI solutions are highly customizable, allowing users with different levels of experience and education to engage with the tools in ways that suit their needs.

PRACTICAL IMPLICATIONS

This research provides valuable insights for a wide range of stakeholders, including HR managers, AI developers, and organizational leaders, regarding the adoption and implementation of AI in talent acquisition. For HR managers, the study highlights the importance of aligning AI tools with organizational values and existing recruitment processes to ensure smooth integration and optimal use. It encourages HR professionals to consider factors such as compatibility, competition, and relative advantages when deciding on AI adoption, thereby enabling a more strategic and effective approach to recruitment.

For AI developers and marketers, the findings emphasize the need to design AI solutions that are user-friendly, secure, and capable of addressing the specific needs of HR professionals. By understanding the factors that influence AI adoption, developers can create more targeted and appealing AI products for the HR sector. Additionally, the study suggests that AI technologies should be developed with a focus on enhancing user experience and increasing the compatibility, which can significantly affect the willingness of organizations to adopt these technologies from an organizational perspective. The study identified that AI adoption in recruitment was significantly influenced by factors like compatibility, competition, relative advantages, and security concerns, which provided a framework for evaluating the ROI of AI investments. Organizations can assess whether these factors translate into tangible improvements in hiring efficiency and accuracy. By leveraging factors such as compatibility, relative advantages, and competitive pressure, organizations can streamline their hiring processes. AI tools reduce time-to-hire and manual effort, ultimately lowering associated costs. So adoption of AI in talent acquisition can play a significant role in controlling the recruitment cost. Moreover, the study's emphasis on demographic moderators such as income, age, education, and professional experience can help in designing performance measurement systems that are more personalized, enabling HR departments to assess how different employee segments respond to AI integration. By linking AI adoption determinants to performance outcomes, the study provides actionable insights for resource allocation, investment justification, and strategic HR planning. From a strategic planning perspective, these insights help leadership prioritize investments in AI technologies that are most likely to yield competitive advantages in attracting and retaining talent. These findings support data-driven decision-making processes, enabling HR and organizational leaders to assess readiness for AI, forecast adoption outcomes, and manage change more effectively. Overall, the research offers a comprehensive framework for understanding the adoption of AI in talent acquisition, serving as a guide for organizations seeking to leverage AI to enhance their HR functions and overall organizational performance.

CONCLUSION

This study has shed light on the usage of AI TA in organizations, particularly within the IT sector. By integrating the Technology-Organization-Environment Framework with demographic variables, the research had empirically tested and validated several hypotheses to comprehend the elements affecting the usage of AI. The findings suggest that compatibility, competition, complexity, top management support, relative advantages, and security & privacy significantly affect the adoption of AI for TA. Furthermore, demographic variables like income, education, age, and experience also had a significant role in building perceptions and the willingness to adopt AI technologies for hiring talent. This study also underscored the importance for AI tool developers and HR managers to collaborate closely in designing user-friendly and secure AI solutions that align with existing organizational processes and values. Understanding the demographic variations in AI adoption can also help in tailoring implementation strategies to specific workforce segments, thereby maximizing the utility and acceptance of AI technologies for talent acquisition. Future research is needed to investigate the extended effect of AI upon excellence of hiring decisions and employee retention, as well as investigate the adoption of AI in other industries and geographic regions.

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