

Received: 28 May 2024, Accepted: 15 June 2024

DOI: <https://doi.org/10.5281/zenodo.13739664>

Artificial Intelligence (AI) for Talent Acquisition (TA) in the Information Technology (IT) Industry of Pakistan: A strategic Planning and Development Imperative

Dr. Sofia Bano

Department of Public Administration, Faculty of Social and Political Sciences, Universitas Airlangga Surabaya, Indonesia.

Email: sofiashaikh@hotmail.com

ORCID: 0000-0002-3894-4758

Dr. Jusuf Irianto

Department of Public Administration, Faculty of Social and Political Sciences, Universitas Airlangga Surabaya, Indonesia

Email: jusuf.irianto@fisip.unair.ac.id

ORCID: 0000-0002-1655-0483

Abstract:

The study aims to investigate the determinants of AI-enabled talent acquisition for improving HR/TA manager's satisfaction with the moderating role of HR readiness in the IT firms of Karachi. 574 responses were collected from the HR and talent acquisition managers of IT firms in Karachi. The results have revealed that Implementing AI-enabled talent acquisition significantly increases the contentment of HR/TA management. Aside from performance expectancy, task-technology compatibility, cost-effectiveness, and effort expectancy all positively impact AI-enabled talent acquisition. However, security and privacy have no such effect. HR readiness moderates the effect of AI-enabled talent acquisition on HR management satisfaction significantly and positively. Effort expectancy, performance expectancy, and task-technology fit all positively and significantly mediate HR/TA management satisfaction. The study has suggested that employees, HR personnel, and TA managers can work closely with IT and cybersecurity departments to implement and maintain the expected cybersecurity policy rules and practice compliance with related regulations.

Keywords: Artificial Intelligence (AI), Talent Acquisition (TA), Information Technology (IT), Pakistan, PLS-SEM.

1. Introduction:

Artificial Intelligence (AI) has garnered significant attention in recent years. This is because of its transformative potential across various industries, including talent acquisition (TA). In the realm of TA, AI offers a plethora of capabilities. These capabilities range from automating

repetitive tasks to analyzing vast datasets. These capabilities are essential for candidate selection and predictive analytics (Vedapradha et al., 2023). Most researchers and practitioners believe that AI could reshape traditional recruitment processes. They had ideas like using AI to speed up laborious tasks and obtain more accurate data. Nevertheless, the AI in TA awaits success even though the premise is straightforward, but the realization of it heavily relies on the other components as well (Al-Surmi et al., 2022).

However, problems like computer security applied only specific skills, and AI inserted in the place of one information technology role demands attention and solutions (Vedapradha et al., 2023). In the Pakistani IT industry, which is experiencing rapid expansion, there is a high need for an experienced workforce; therefore, adopting artificial intelligence by the TA will be an excellent advantage for Pakistani IT firms. However, challenges such as the absence of resources, antiregulatory measures, and resistance to change from cultural norms might slow down the rapid application of this technology (Ali & Xie, 2021). Therefore, understanding the interplay between multiple variables is crucial for realizing the full potential of AI in talent acquisition within the Pakistani IT industry.

Regarding the practical aspects of HR/TA manager satisfaction, artificial intelligence might be considered unsuitable for cycling talent search. The speed of development of AI technologies may lead to difficulties for HR and TA managers because they will find themselves in situations when they cannot comprehend how to employ these tools to analyze applicants (França et al., 2023). This veil of unfamiliarity can confuse managers with negative feelings and cause dissatisfaction with the meaning of AI-integrated TA systems (Allal-Chérif et al., 2021). HR/TA managers could find it challenging to deal with the problems related to data quality, completeness, and relevance, which makes it harder for AI algorithms to perform an excellent job of selecting and recruiting the best-dedicated workers (Budhwar et al., 2022).

AI could inadvertently reinforce any pre-existing biases in the hiring process. This could defeat the very purpose of digital reinforcement to aid equality and amplify inequalities across talents (Harisha et al., 2023). Managers in HR/TA departments face the unintended consequences of AI algorithms that could look for a quota of people from different backgrounds or simply reproduce the general biases of the recruitment system by just favoring specific demographics. Such biases can only be mitigated through inclusive oversight and tracking procedures, increasing the complexity of the HR/TA manager's task (Budhwar et al., 2022).

Moreover, the dynamic nature of the IT industry in Pakistan presents ongoing challenges for HR/TA managers. These challenges are tasked with talent acquisition. Rapid technological changes, market demands, and skill requirements necessitate agility and adaptability in recruitment strategies (Shakeel & Siddiqui, 2021). AI empowers companies to elevate organizational agility through data analytics and enhancing automation. However, as a drawback to this, HR/TA professionals will oversee AI tools and adaptations to quickly adjust to the contemporary environment, which may and can elevate pressure and decrease satisfaction (França et al., 2023).

Currently, researchers have mainly focused on researching the field of applying AI in talent acquisition in the IT domain that looks at technological advancement and benefits associated with the adoption of AI (Allal-Chérif et al., 2021; França et al., 2023; Wongras & Tanantong, 2023). Some studies have investigated the impact of AI on different aspects of the recruitment process (Chen, 2023): candidate sourcing (Ore & Sposato, 2022) and organizational performance (Lin et al., 2022). This research intends to fill this gap in knowledge through an empirical and structured exploration of factors assessing HR/TA managers' satisfaction with AI-assisted talent acquisition in IT companies, focusing on HR's readiness to use AI as a moderating factor. This directs to accounting for the behavioral complexity of AI adoption in talent acquisition processes. Through empirical analysis and practical applications, it is envisaged that this study will sift actionable recommendations to improve HR/TA manager satisfaction and maximize AI capacity use in talent acquisition within IT enterprises (Shahzad et al., 2023).

1.1. Research Objective

The study aims to investigate the determinants of AI-enabled talent acquisition for improving HR/TA manager's satisfaction with the moderating role of HR readiness in the IT firms of Karachi.

1.2. Research Questions

1. What are the determinants of AI-enabled talent acquisition among HR and talent acquisition managers towards HR/TA managers' satisfaction in the IT firms of Karachi?
2. Does HR readiness moderate the effect of AI-enabled talent acquisition and HR/TA managers' satisfaction?

2. Literature Review

2.1. Unified Theory of Acceptance and Use of Technology (UTAUT)

The unified theory of acceptance and use of technology (UTAUT) was proposed by Venkatesh et al. (2003). UTAUT is a widely recognized theoretical framework. This framework seeks to explain and predict individuals' acceptance and use of technology in organizational settings. It integrates elements from various existing theories. These theories include the theory of reasoned action, the technology acceptance model, and the innovation diffusion theory. These theories comprehensively understand technology adoption behaviors (Chakraborty & Al Rashdi, 2018).

Regarding AI, an enabler of Talent Acquisition in the IT industry, UTAUT's role as a theoretical framework in analyzing the satisfaction levels of HR/TA managers with AI adoption is indispensable. The human resource/ talent acquisition managers' role is to predict performance expectancy in the research objective area. We want to discover all the conditions that can satisfy the HR/TA manager with the AI specialist who facilitates talent acquisition through conducting research (Chakraborty & Al Rashdi, 2018). Regarding effort expectancy, the perceived ease of using AI technologies becomes a significant factor in making commentators more comfortable. If AI can be implemented, it will become more practicable

for managers to employ it for talent acquisition (Venkatesh et al., 2003). Hence, UTAUT is a framework that can be used theoretically to analyze the complicated interaction of variables influencing the technology acceptance/usage of HR management tools (Wongras & Tanantong, 2023).

2.2. Development of the Hypotheses

2.2.1. AI-Enabled TA and HR/TA Managers' Satisfaction

AI-enabled talent acquisition refers to using AI technologies. Furthermore, it refers to the algorithms employed by an organization to recognize, engage, and choose candidates for vacant positions. During recruitment, AI is used for many tasks, such as screening resumes, matching candidates, analyzing data to make predictions, and automated communication (Grover, 2022). HR/TA manager satisfaction refers to the subjective evaluation of HR and talent acquisition managers' overall contentment. It also allows fulfillment with the processes, outcomes, and experiences related to talent acquisition activities within their organizations (Batra, 2023).

The link between AI-powered talent acquisition and HR/TA manager satisfaction often demonstrates that AI technologies boost the performance and effectiveness of talent acquisition processes (Black & van Esch, 2021). These advantages are expected to enhance professional accomplishment and satisfaction in TA and HR managers by enabling them to perform their roles more appropriately, realize organizational objectives, and satisfy their professional obligations and duties (Allal-Chérif et al., 2021). Hence, it has been hypothesized that:

H1. AI-enabled TA has a significant effect on HR/TA managers' satisfaction.

2.2.2. Performance Expectancy, AI-Enabled TA, and HR/TA Managers' Satisfaction

Performance expectancy implies that an individual's estimated utility and payoff might be due to using a particular techno or computing system (Horodyski, 2023). HR and talent acquisition professionals define performance expectancy in ATA as the level of belief about the instrumental undertaking of AI technologies to enhance recruitment processes and the receipt of positive outcomes. This was associated with the ability of AI to hone the process of making candidate screening more effective, making candidate matching important, providing data-driven insights for decision-making, and optimizing the talent acquisition process (Tanantong & Wongras, 2024).

In this regard, researchers note that TA and HR managers' understanding of AI technology's usefulness and benefits is crucial in their readiness to embrace AI in summing up talents. Significant levels of performance expectancy would increase the integration of the AI-driven TA systems rather than the other systems that are not AI and would lead to AI-enabled recruitment technology that will be accepted much faster in the organization (Sattu et al., 2024).

So, an AI-based TA as an interlocutor speaks about the positive effects of performance expectancy on an HR/TA manager's satisfaction (Tanantong & Wongras, 2024). Hence, it has been hypothesized that:

- H2. Performance expectancy has a significant effect on AI-enabled TA.
- H3. AI-enabled TA mediates the effect of performance expectancy on HR/TA managers' satisfaction.

2.2.3. Effort Expectancy, AI-Enabled TA, and HR/TA Managers' Satisfaction

The concept of effort expectancy is characterized by its simplicity and ease of use, suggesting that the performer's behavior is attributed to the attribute of ease of use. The widespread implementation of AI-powered talent acquisition techniques by HR and TA departments is heavily impacted by the perceived ease of use (Tanantong & Wongras, 2024). A manager who considers AI simple to apply and understand becomes friendlier and willing to apply and integrate this technology into the recruitment process. A pronounced commitment to effort expectancy of such technologies means more AI-based TA systems to be adopted by managers who believe that the technologies are, on the other hand, convenient and user-friendly (Chiu et al., 2021).

Additionally, AI-enabled TA serves as a mediator. This mediation translates the effect of effort expectancy into HR/TA managers' satisfaction. When HR and TA managers find AI-enabled TA systems easy to use, they experience higher satisfaction with the talent acquisition process and overall job fulfillment (Chowdhury et al., 2022). As a consequence, and being led by AI, TA underscores the favorable performance of agency expectancy on the satisfaction level of HR and TA managers in their work by increasing the effectiveness and productivity of talent acquisition processes. Further, the same results are witnessed by the HR and TA managers (Tanantong & Wongras, 2024). Hence, it has been hypothesized that:

- H4. Effort expectancy has a significant effect on AI-enabled TA.
- H5. AI-enabled TA mediates the effect of effort expectancy on HR/TA managers' satisfaction.

2.2.4. Cost-Effectiveness, AI-Enabled TA, and HR/TA Managers' Satisfaction

As a consequence, and being led by AI, TA underscores the favorable performance of agency expectancy on the satisfaction level of HR and TA managers in their work by increasing the effectiveness and productivity of talent acquisition processes. Research on this topic proves that the component of effort expectancy is the driving force that leads to the acceptance of AI-based talent acquisition (Malik et al., 2022). The significant effect of cost-effectiveness on AI-enabled TA adoption is evident. When AI technologies are perceived as cost-effective, managers are more inclined to adopt them in recruitment processes (Sattu et al., 2024).

Another result of AI-powered TA is that it contributes to cost-effectiveness and affects how content HR/TA managers are. Managers with a positive picture of AI-supported efficiency tend to be happier with talent acquisition and overall job (Sattu et al., 2024). This satisfaction stems from the recognition that adopting cost-effective AI solutions improves recruitment efficiency and optimizes resource utilization within the organization (Budhwar et al., 2022). This shows that AI-enabled TA becomes an avenue to bring multiplying positive effects of optimization onto HR/TA managers' assessment of their work by increasing recruitment processes'

efficiency and effectiveness and minimizing the related costs (Malik et al., 2022). Hence, it has been hypothesized that:

H6. Cost-effectiveness has a significant effect on AI-enabled TA.

H7. AI-enabled TA mediates the effect of cost-effectiveness on HR/TA managers' satisfaction.

2.2.5. Privacy/Security, AI-Enabled TA, and HR/TA Managers' Satisfaction

Privacy/security means understanding that the channel should be protected from unauthorized access or misuse of important data. When important things like the security and privacy of AI technology are given priority, more HR and TA managers are likely to use these technologies in their systems. They feel the AI components can guard candidate information and ensure confidentiality. (Holzinger et al., 2021). In the succeeding step, AI-aided TA facilitates managers' understanding of the ambitious aspects of privacy/security on HR/TA managers' satisfaction. If HR and TA managers feel AI-based TA systems are highly secure and accustomed to privacy, they experience higher satisfaction in the recruitment process (Murdoch, 2021). The assurance on the end of the human resource personnel and job hopefuls that AI systems are done credibly gives rise to trust and builds on satisfaction with the talent acquisition process. So, AI-driven TA is conceived as placing confidence and trust in HR/TA managers by ensuring them the ability to get reliable and secure workflow, which increases their overall job satisfaction (Kaur & Gandolfi, 2023). Hence, it has been hypothesized that:

H8. Privacy/security has a significant effect on AI-enabled TA.

H9. AI-enabled TA mediates the effect of privacy/security on HR/TA managers' satisfaction.

2.2.6. Task-Technology Fit, AI-Enabled TA, and HR/TA Managers' Satisfaction

Task technology fit indicates how much a technology suits assigned tasks or activities. In this view, technology is an efficient fit if its capabilities align with user needs (Vendramin et al., 2021). A case of oversized task-technology fit in AI-automated talent acquisition (TA) tools is considered, which leads them to deem the technologies as on the right lines of support for their recruitment tasks. An alignment of the technology with the recruitment manager's expectations increases the likelihood of practical adoption of AI systems, as they are confident that these systems will effectively address their specific hiring issues (Faqihi & Miah, 2022).

AI-empowered job activities increase the satisfaction of Human Resource/Talent Acquisition (HR/TA) managers. It is said that the perception of harmony between the expertise of AI technology in intelligence-aided recruiting and their responsibilities raises the level of satisfaction from the hiring process (Faqihi & Miah, 2022; Jiang et al., 2023). As a consequence, the quality of Task-Technology Fit of AI-enabled TA will also lead to the increased satisfaction of HR/TA managers because the provided technology is adjusted to their recruitment job tasks, as a result contributing to their overall contentment Faqihi and Miah (2022). Hence, it has been hypothesized that:

- H10. Task-technology fit has a significant effect on AI-enabled TA.
 H11. AI-enabled TA mediates the effect of task-technology fit on HR/TA managers' satisfaction.

2.2.7. Moderating Role of HR Readiness between AI-Enabled TA and HR/TA Managers' Satisfaction

HR readiness is the organization's ability to allocate new technologies to the need. Organizations with high levels of HR readiness see that AI-empowered recruitment systems are better integrated into TA-HRM, which, in turn, boosts both TA and HR managers' satisfaction (Sattu et al., 2024). However, on the other hand, in the workflow with lower HR readiness, the influence of AI-stuffed TA on satisfaction is usually restricted due to resource shortage or resistance to change. Hence, HR readiness reduces the effect of AI-enabled TA on HR/TA managers' satisfaction by altering organizations' skills to mobilize and exercise the technologies to improve new talent acquisition processes (Mohapatra et al., 2023). Hence, it has been hypothesized that:

- H12. HR readiness moderate the effect of AI-enabled TA and HR/TA managers' satisfaction.

2.1. Research Framework

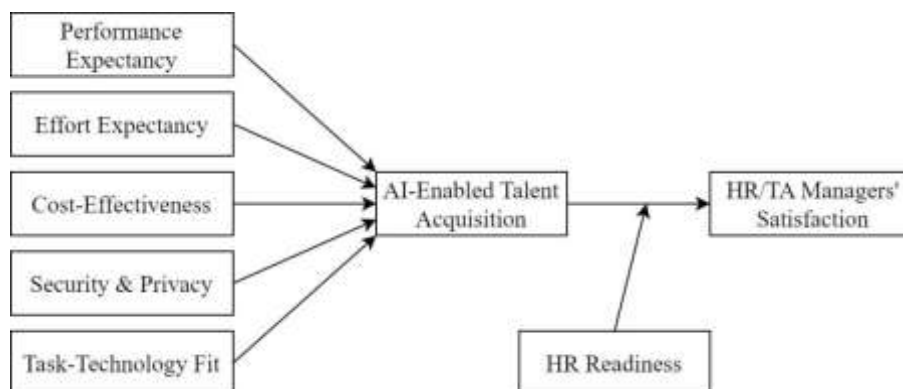


Figure 1: Research Model

3. Methodology

3.1. Sampling Design

The research sample would include the HR and talent acquisition managers in IT firms in Karachi, Pakistan. Firstly, the research focuses on the individuals who fill managerial recruitment positions and oversee IT companies' recruiting process. This is the target population (Hussain et al., 2022). Purposive sampling is one of the non-probabilistic sampling techniques, and the selection of the participants is based on specific characteristics or criteria directly related to the research aims. The present research has purposely chosen HR managers and personnel with the experience and expertise in integrating AI technology into their businesses (Guarte & Barrios, 2006).

The investigators aim to interview HR personnel who are personally impacted by technology implementation and talent acquisition processes. These HR practitioners will be a source of personal, detailed, and specific information needed to identify the causes of HR/TA manager satisfaction and the moderating role of HR readiness as these managers will give their viewpoints. Utilizing this method makes it possible to have a sample with a varied background and the expertise needed to analyze the research questions thoroughly. Beyond that, in sampling for a purpose, participants from different cultures and contexts can be recruited to meet this aim, as this adds depth and breadth to the study outcomes (Rai & Thapa, 2015).

The unit of analysis is being chosen as an individual. The primary motive of the study is to understand the perceptions, attitudes, and behaviors of HR and talent acquisition managers within IT firms regarding AI-enabled talent acquisition and HR readiness from an individual basis. Sharing people is one of the research methods used to study their experiences, perspectives, and judgment, which is all about meeting the research objectives on a personal level (Rai & Thapa, 2015). Table 1 shows the demographic profile of the 574 respondents.

Table 1: Demographic Profile (n = 574)

		Frequency	Percent
Gender	Male	274	47.7
	Female	300	52.3
Age Group	18-25 years	146	25.4
	26-35 years	134	23.3
	36-45 years	146	25.4
	45+ years	148	25.8
Education Level	Bachelor's Degree	176	30.7
	Master's Degree	196	34.1
	Post-Master's Degree	202	35.2
Years of Experience in HR/Talent Acquisition	Less than 1 year	109	19.0
	1-5 years	105	18.3
	6-10 years	111	19.3
	11-15 years	114	19.9

	More than 15 years	135	23.5
	HR Manager	151	26.3
Position/Job Title	Talent Acquisition Manager	150	26.1
	HR Executive	144	25.1
	Talent Acquisition Specialist	129	22.5
	Software Development	120	20.9
	IT Consulting	105	18.3
Type of IT Firm	Hardware/Infrastructure	123	21.4
	IT Services	126	22.0
	Others	100	17.4
	Small (1-50 employees)	210	36.6
Company Size (Number of Employees)	Medium (51-250 employees)	170	29.6
	Large (251+ employees)	194	33.8
	Basic	185	32.2
Technology Proficiency	Intermediate	179	31.2
	Advanced	210	36.6
Previous Experience with AI in HR	Yes	285	49.7
	No	289	50.3

3.2. Measures

Table 2 shows the measures and instrumentation of the data collection tool.

Table 2: Instrument

Variable Name	N Items	Likert Type	Source
---------------	---------	-------------	--------

Performance Expectancy	3	5-Points	(Ekka & Singh, 2022)
	1	5-Points	(Rahi et al., 2019)
Effort Expectancy	3	5-Points	(Ekka & Singh, 2022)
	1	5-Points	(Rahi et al., 2019)
Cost-Effectiveness	8	5-Points	(Pillai & Sivathanu, 2020)
Security & Privacy	2	5-Points	(Pillai & Sivathanu, 2020)
	1	5-Points	(Rahi et al., 2019)
Task-Technology Fit	7	5-Points	(Pillai & Sivathanu, 2020)
AI-Enabled TA	5	5-Points	(Pillai & Sivathanu, 2020)
HR Readiness	4	5-Points	(Pillai & Sivathanu, 2020)
HR/TA Managers Satisfaction	4	5-Points	(Kambur & Akar, 2022)

3.3. Data Collection

A Likert scale of 5 points is one of the main tools for recording survey responses where the subjects are asked to estimate their agreement or disagreement about certain statements. Participants can provide qualitative representations of their thoughts or attitudes by rating each statement on a five-point Likert scale that ranges from "Strongly Disagree" to "Strongly Agree" (Russo et al., 2021). Among the many types of scales, the 5-point Likert scale is chosen because of its clear form, ease of reading, and the ability to measure different types of answers without straining the participants. It captures detailed perceptions and practical implications regarding AI talent acquisition and how individuals can cope with them (Alhassn et al., 2022).

The survey method was deemed most appropriate to achieve the research goals of a given research study as it provides data from a large sample size in a short timeframe. Researchers can address a broader range of perspectives, as survey results would come from HR and TQ managers in Karachi's IT firms. They would contain perceptions, experiences, and attitudes towards AI regarding recruitment and HR scoring (Morgan & Harmon, 2001). Surveys provide an instrument of data gathering in which a standardized approach is responsible for its unity in defining variables for different respondents. Thus, the 5-point Likert scale, as well as the use of the cross-sectional survey method, dramatically simplifies the process of data collection, helping academic researchers to gather all the necessary information and explore the impact of AI on HR in the IT industry of Pakistan (Ning et al., 2023).

3.4. Data Analysis

Hair et al. (2017) stated that PLS-SEM evaluates the extent to which the model accurately explains the target constructs of interest and calculates the correlation between the latent variables. PLS-SEM can estimate highly complex models due to its adaptable data requirements. Complex models with numerous variables and indicators, higher-order constructs, formative assessment, and mediation and moderation effects are more suitable for investigating and predicting categorical or ordinal data (Hair et al., 2019). PLS-SEM enables researchers to develop and assess complex cause-effect models utilizing latent and observed variables. Additionally, the study conducted by Hair Jr et al. (2017) provides a precise assessment of outcomes and their predictive capacity by considering many variables. Therefore, the current study will utilize Partial Least Squares Structural Equation Modelling (PLS-SEM) for data analysis. The purpose of utilizing this methodology is to examine a small sample size in order to provide effective and significant results.

4. Results and Findings

4.1. Measurement Model

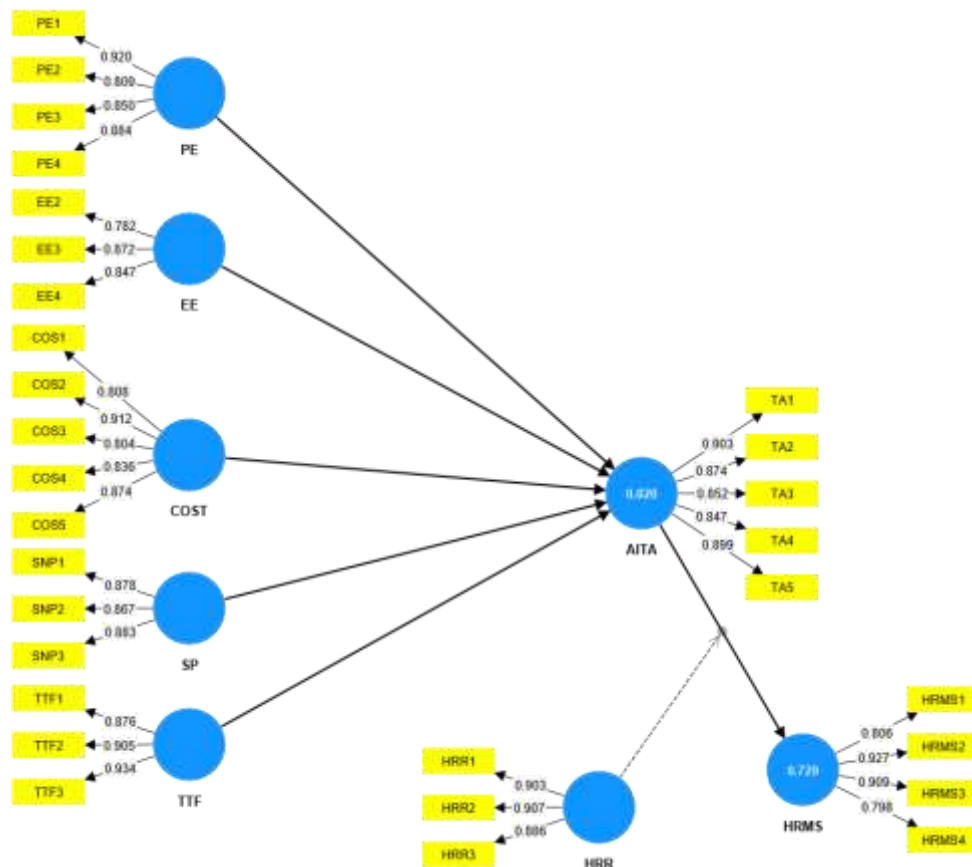


Figure 2: PLS Algorithm using SmartPLS v4

4.1.1. Construct and convergent validity

Table 4 evaluates the measurement model's construct and convergent validity using estimates from the PLS method.

Table 3: Measurement Model

	Loadings	Prob.	VIF	Alpha	CR	AVE
COS1 <- COST	0.808	0.000	2.679			
COS2 <- COST	0.912	0.000	3.593			
COS3 <- COST	0.804	0.000	2.417	0.903	0.927	0.719
COS4 <- COST	0.836	0.000	2.607			
COS5 <- COST	0.874	0.000	3.042			
EE2 <- EE	0.782	0.000	1.638			
EE3 <- EE	0.872	0.000	1.608	0.787	0.873	0.696
EE4 <- EE	0.847	0.000	1.710			
HRMS1 <- HRMS	0.806	0.000	2.110			
HRMS2 <- HRMS	0.927	0.000	4.169	0.883	0.920	0.743
HRMS3 <- HRMS	0.909	0.000	3.085			
HRMS4 <- HRMS	0.798	0.000	2.439			
HRR1 <- HRR	0.903	0.000	2.508			
HRR2 <- HRR	0.907	0.000	2.421	0.881	0.926	0.807
HRR3 <- HRR	0.886	0.000	2.427			
PE1 <- PE	0.920	0.000	4.485			
PE2 <- PE	0.809	0.000	2.013	0.889	0.923	0.751
PE3 <- PE	0.850	0.000	3.046			

PE4 <- PE	0.884	0.000	3.049			
SNP1 <- SP	0.878	0.000	1.797			
SNP2 <- SP	0.867	0.000	2.291	0.850	0.908	0.767
SNP3 <- SP	0.883	0.000	2.433			
TA1 <- AITA	0.903	0.000	3.511			
TA2 <- AITA	0.874	0.000	3.034			
TA3 <- AITA	0.852	0.000	2.808	0.923	0.942	0.766
TA4 <- AITA	0.847	0.000	2.706			
TA5 <- AITA	0.899	0.000	3.583			
TTF1 <- TTF	0.876	0.000	2.217			
TTF2 <- TTF	0.905	0.000	2.847	0.890	0.932	0.820
TTF3 <- TTF	0.934	0.000	3.370			

Hair et al. (2011b); Hair et al. (2019) recommended that outer loadings exceed 0.70, while the average variance extracted (AVE) and composite reliability (CR) should both surpass 0.50 and 0.70, respectively. The table above shows loadings greater than 0.70 and VIFs less than 5 for the markers. (Hair et al., 2011a). The above table demonstrates a probability level under 5% and a VIF below 5 (Hair et al., 2011a). Additionally, the alpha coefficient for each latent construct is more significant than 0.70. In the above table, all indicators and constructs have achieved the suggested thresholds; henceforth, constructs were developed adequately, whereas convergent validity has also been achieved.

4.1.2. Discriminant Validity

Table 5 shows the results of the FLC for the evaluation of discriminant validity.

Table 4: Fornell-Larcker Criterion (FLC)

	AITA	COST	EE	HRMS	HRR	PE	SP	TTF
AITA	0.875							
COST	0.801	0.848						

EE	-0.643	-0.748	0.834					
HRMS	0.839	0.686	-0.581	0.862				
HRR	0.824	0.833	-0.680	0.769	0.898			
PE	0.727	0.584	-0.669	0.756	0.619	0.867		
SP	0.726	0.787	-0.686	0.634	0.717	0.609	0.876	
TTF	0.850	0.743	-0.703	0.763	0.834	0.719	0.745	0.905

Fornell and Larcker (1981) recommended that the square root of the average of latent constructs (represented by bold values) exceeds the correlation with other constructs (represented by non-bold values). This finding suggests that the theoretical constructs of the indicators exhibit a greater degree of shared variation in comparison to other indicators (Ab Hamid et al., 2017; Cheung & Wang, 2017). Hair et al. (2011a) suggest that the square root of the AVE coefficient for a construct is more significant than its correlation coefficient with other constructs, provided that the construct has demonstrated its uniqueness within the structural model (Fornell & Larcker, 1981). This is illustrated in the table above. Consequently, discriminant validity has been established utilizing FLC.

HTMT ratio

The outcome of HTMT ratio to evaluate discriminant validity is presented in Table 6.

Table 5: HTMT Ratio

	AITA	COST	EE	HRMS	HRR	PE	SP	TTF
AITA								
COST	0.861							
EE	0.728	0.857						
HRMS	0.921	0.760	0.681					
HRR	0.909	0.934	0.778	0.868				
PE	0.804	0.634	0.775	0.856	0.691			
SP	0.805	0.888	0.822	0.739	0.819	0.684		

TTF	0.937	0.816	0.821	0.861	0.937	0.808	0.849
-----	-------	-------	-------	-------	-------	-------	-------

Table 4.6 displays the results of the HTMT ratio for assessing discriminant validity. Henseler et al. (2016); Henseler et al. (2015) provide an adequate level of differentiation between latent constructs; it is advised to keep the HTMT ratio below 0.90. Therefore, the highest HTMT ratio of 0.868 is between HRR and HRMS.

4.1.3. Predictive Power of the Endogenous Constructs

Table 7 shows the predictive power using the PLS algorithm technique.

Table 6: Predictive Power

	R-Square	R-Square Adjusted
AI-Enabled Talent Acquisition	0.820	0.819
HR/TA Managers Satisfaction	0.729	0.727

Chin (1998) recommended R^2 values for endogenous latent variables; more than or equal to 0.67 is considered substantial, more than 0.33 was considered moderate, and less than or equal to 0.19 was deemed weak. Here, AI-enabled talent acquisition and HR/TA manager's satisfaction have a substantial predictive power of more than 0.67, i.e., 0.820 and 0.729, respectively.

4.2. Structural Model

4.2.1. Direct-Effect Analysis using PLS Path Modeling

Table 4.8 shows the PLS bootstrapping hypothesis testing direct-effect analysis findings.

Table 7: Direct-Effect Analysis

	Estimate	S. D.	t-Stats	Prob.	Decision
AITA -> HRMS	0.635	0.037	17.194	0.000	Supported
COST -> AITA	0.446	0.028	15.840	0.000	Supported
EE -> AITA	0.195	0.025	7.819	0.000	Supported

PE -> AITA	0.260	0.022	11.858	0.000	Supported
SP -> AITA	0.003	0.030	0.104	0.917	Not Supported
TTF -> AITA	0.467	0.025	18.409	0.000	Supported

PE = Performance Expectancy; EE = Effort Expectancy; COST = Cost-Effectiveness; SP = Security & Privacy; TTF = Task-Technology Fit; AITA = AI-Enabled TA; HRMS = HR/TA Managers Satisfaction.

In the table, the beta coefficient of 0.635 and p-value of less than 0.05 suggest that AITA positively affects HRMS. Positive and statistically significant, "COST" effects "AITA" with a beta coefficient of 0.446 and a p-value below 0.05. Electrical engineering (EE) positively affects the Academic Index of Technical Abilities (AITA) with a p-value below 0.05 and a coefficient of 0.195. A substantial positive association exists between physical education (PE) and user attitude (AITA), with a p-value below 0.05 and a correlation coefficient (ω) of 0.260. SP has a negligible influence on AITA (p-value > 0.05, coefficient 0.003). TTF favorably affects AITA, as shown by the coefficient of 0.467 and p-value below 0.05.

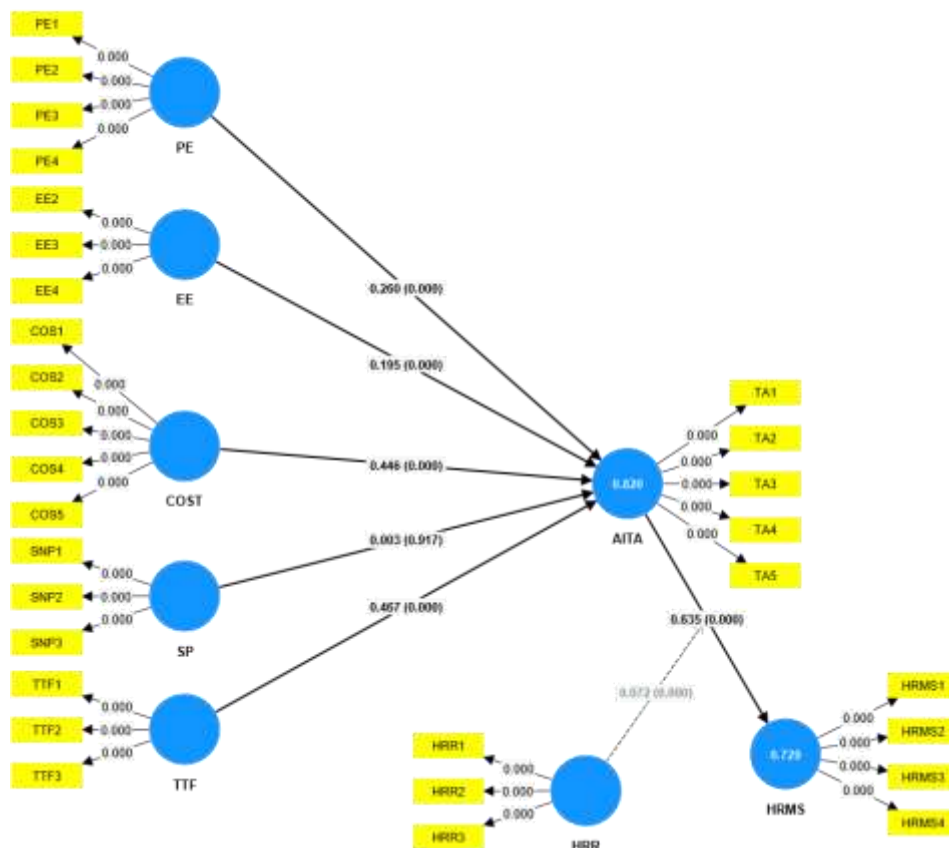


Figure 3: PLS Bootstrapping using SmartPLS v4

4.2.2. Specific Indirect-Effect Analysis using PLS Path Modeling

Table 9 shows the result of mediation hypothesis testing based on specific indirect-effect analysis using PLS path modeling.

Table 8: Specific Indirect-Effect Analysis

	Estimate	S. D.	t-Stats	Prob.	Decision
COST -> AITA -> HRMS	0.283	0.023	12.293	0.000	Supported
EE -> AITA -> HRMS	0.124	0.018	6.931	0.000	Supported
PE -> AITA -> HRMS	0.165	0.020	8.106	0.000	Supported
SP -> AITA -> HRMS	0.002	0.019	0.103	0.918	Not Supported
TTF -> AITA -> HRMS	0.297	0.025	12.058	0.000	Supported

PE = Performance Expectancy; EE = Effort Expectancy; COST = Cost-Effectiveness; SP = Security & Privacy; TTF = Task-Technology Fit; AITA = AI-Enabled TA; HRMS = HR/TA Managers Satisfaction.

As shown in the data above, AITA mediates the effect of COST on HRMS in a significant and positive manner ($\beta = 0.283$, $p < 0.05$). AITA mediates the relationship between EE and HRMS significantly and positively ($\beta = 0.124$, $p < 0.05$). AITA positively and significantly mediates the relationship between PE and HRMS ($\beta = 0.165$, $p < 0.05$). AITA positively and insignificantly mediates the effect of SP on HRMS ($\beta = 0.002$, $p > 0.05$). Additionally, the impact of TTF on HRMS is significantly and positively mediated by AITA, as indicated in the table above ($\beta = 0.297$, $p < 0.05$).

4.2.3. Moderation Analysis using PLS Path Modeling

Table 10 shows the result of moderation analysis using PLS path modeling.

Table 9: Moderation Analysis

	Estimate	S. D.	t-Stats	Prob.	Decision
HRR x AITA -> HRMS	0.072	0.015	4.933	0.000	Supported

AITA = AI-Enabled TA; HRMS = HR/TA Managers Satisfaction; HRR = HR Readiness.

Above table showed that HRR ($\beta = 0.072, p < 0.05$) positively moderates the effect of AITA on HRMS. This provided that increasing HR readiness towards AI integration in HR and TA processes enhances HR/TA Managers' Satisfaction due to AI-enabled TA.

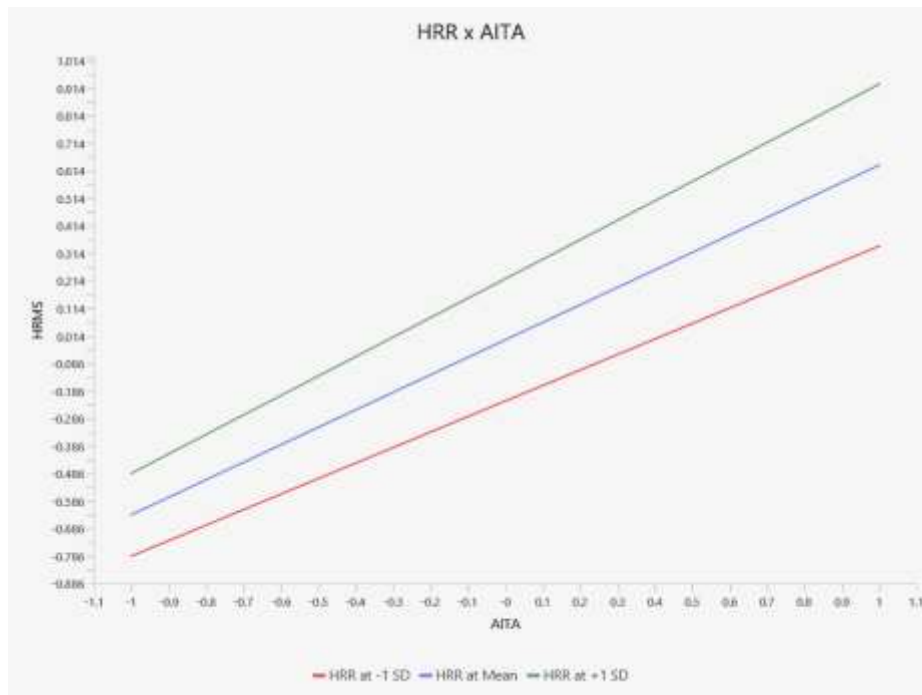


Figure 4: Moderation Graph using SmartPLS v4

4.2.4. Predictive Relevance of the Endogenous Constructs

Table 11 shows the predictive relevance of the endogenous constructs in the structural model using PLS predict estimations.

Table 10: Predictive Relevance

	Q-Square
AI-Enabled Talent Acquisition	0.817
HR/TA Managers Satisfaction	0.674

Hair et al. (2013) recommended that $Q^2 > 0.02$ indicates weak relevance, $Q^2 > 0.15$ indicates moderate relevance, and $Q^2 > 0.35$ indicates strong relevance. The above table demonstrates that AI-enabled talent acquisition and HR/TA managers' satisfaction have strong relevance of 0.817 and 0.674, respectively, as both the values are above 0.35.

5. Discussions

The findings indicate that AITA has a strong and favorable impact on HRMS. This outcome is in line with Grover (2022). This is because AI-enabled talent acquisition streamlines recruitment processes enhance candidate sourcing, and improves decision-making through data-driven insights. By leveraging artificial intelligence technologies, HR professionals can significantly reduce the time-to-fill positions, identify top talent more efficiently, and optimize resource allocation. These benefits directly enhance HR/TA manager's satisfaction with the HR management system. Integrating AI enhances system effectiveness, user experience, and organizational outcomes. As a result, the positive impact of AI-enabled talent acquisition on HRMS satisfaction is evident and significant in improving HR operations (Batra, 2023).

According to the research results, COST substantially and positively affects AITA. This conclusion is supported by Malik et al. (2022). Adopting AI-enabled talent acquisition is influenced directly by the perceived cost-effectiveness of integrating new technology. Businesses are more inclined to invest in AI solutions because the potential advantages outweigh the technology's expenses. This favorable impression of cost-effectiveness encourages organizations to use AI in talent acquisition procedures, as they anticipate increased productivity, lower recruiting expenses, and better results. The notion that cost significantly and positively affects AI-enabled talent acquisition suggests that businesses should prioritize investing in AI technology when they see a greater return on investment than they do (Sattu et al., 2024).

Furthermore, EE has a substantial favorable impact on AITA. The result achieved is consistent with Chiu et al. (2021). The reason is that effort expectancy directly influences the adoption of AI-enabled talent acquisition. When individuals perceive that using AI technologies in talent acquisition processes requires minimal effort and is easy to use, they are more inclined to embrace such solutions. A user-friendly interface, intuitive design, and seamless integration of AI features reduce the perceived effort associated with adopting new technologies. Consequently, personnel are more likely to adopt and effectively employ AI-driven technologies in talent acquisition, leading to advantageous outcomes such as heightened efficiency, improved decision-making, and streamlined processes. Therefore, effort expectancy significantly impacts adopting AI-enabled talent acquisition (Chowdhury et al., 2022).

Positively and significantly, PE influences AITA. This finding is substantiated by Tanantong and Wongras (2024). When people believe integrating AI into their work will enhance their performance and help meet organizational goals, they are more likely to adopt these technologies. Cheerful anticipations of AI benefits, like increased efficiency, improved decision-making, and better outcomes, motivate individuals to embrace AI in talent acquisition. Therefore, the perceived advantages of AI adoption directly shape people's attitudes and willingness to incorporate AI technologies into their talent acquisition strategies (Horodyski, 2023).

Similarly, SP has a negligible impact on AITA. This finding aligns with the research conducted by Holzinger et al. (2021). One likely reason is that the implementation of AI-powered talent acquisition is not significantly affected by concerns related to security and privacy. Even though security and privacy in HR procedures are essential, people may prioritize other considerations—like performance or usability- when deciding whether to embrace AI technologies. On the other hand, companies may already have robust security protocols in place, allaying worries about data privacy related to the use of AI. Therefore, other variables may significantly influence adoption decisions more than security and privacy, making the perceived impact of these considerations on AI-enabled talent acquisition negligible (Murdoch, 2021).

Similarly, the variable TTF strongly and positively impacts the variable AITA. This finding is corroborated by Vendramin et al. (2021). The potential rationale for the beneficial solid impact of task-technology fit on AI-enabled talent acquisition is its direct influence on the alignment between technology features and HR tasks. When HR professionals perceive that AI technologies effectively support their tasks, such as candidate screening or predictive analytics, they are more likely to adopt them. A strong fit between technology capabilities and job requirements enhances user satisfaction, increases efficiency, and improves decision-making. Consequently, HR professionals recognize the value of AI-enabled tools in streamlining talent acquisition processes, leading to widespread adoption. Therefore, task-technology fit significantly contributes to adopting AI-enabled talent acquisition (Faqihi & Miah, 2022).

In addition, AITA plays a crucial role in mitigating the impact of COST on HRMS substantially and favorably. This outcome is in line with Sattu et al. (2024). The cause of this is that AI-based talent acquisition is a very important "middleman" between the effectiveness of the system in cost terms and the satisfaction level of HR management. Suppose businesses think about the cost-efficiency advantage of AI technologies as positively impacting their talent acquisition activities. In that case, they are, therefore, more inclined to broaden their spending on those processes. The productivity of AI-driven talent acquisition is commensurate with cost reduction and outcome improvements, which positively impacts HR and TA managers. Thus, the role of AI-driven talent acquisition as a mediator makes AI technology more critical in practice by transforming the perceived cost-effectiveness of AI technologies into the actual process of improvement of HRM satisfaction, hence, more customer satisfaction among HR and talent acquisition managers (Budhwar et al., 2022).

Attitude towards Artificial Intelligence (AITA) significantly and positively moderates the effect of Employee Engagement (EE) on HRMS. Evidence supports this conclusion, Chowdhury et al. (2022). The possible explanation for the result is that AI-enabled talent acquisition is a significant mediator between effort expectancy and HR management system satisfaction. When users perceive that adopting AI technologies in talent acquisition processes requires minimal effort and is easy to use, they are more likely to embrace such solutions. As AI-enabled talent acquisition enhances user experience, reduces complexity, and improves efficiency, it directly influences HRM satisfaction. Therefore, the mediating effect of AI-enabled talent acquisition highlights its crucial role in translating the seeming ease of using AI

technology into tangible improvements in HRMS satisfaction, ultimately leading to enhanced overall satisfaction among HR and Talent Acquisition managers (Chiu et al., 2021).

Similarly, AITA effectively moderates the impact of PE on HRMS well. This outcome is in line with Horodyski (2023). What gives AITA its paramount and favorable reinforcement effect on performance expectancy to HR management system satisfaction is the tendency for users to agree that adopting AI technologies will improve their performance. Thus, they are more likely to accept such ideas. As AI-powered talent acquisition can speed up the recruitment processes while making decisions and being more effective, it can be considered one of the reasons that ensure the satisfaction of HRMS. In this way, through the mediation effect of AI-enabled talent acquisition, the role of AI in turning the perceived benefits into actual improvements in HRM satisfaction is emphasized. So, this can end up enhancing the level of satisfaction among the HR and the talent acquisition managers, increasing the overall satisfaction (Sattu et al., 2024).

Positively and insignificantly, AITA mediates the impact of SP on HRMS. This finding is substantiated by Murdoch (2021). Despite the importance of security and privacy considerations in HR processes, the perceived benefits of AI adoption may not directly translate into improved satisfaction with HRMS. Security and privacy concerns may remain significant even with the implementation of AI technologies. Therefore, the mediation effect of AI-enabled talent acquisition on security and privacy's influence on satisfaction is limited. This indicates that other factors may play a more dominant role in shaping HR/talent acquisition managers' satisfaction levels (Holzinger et al., 2021).

Furthermore, AITA effectively and favorably moderates the impact of TTF on HRMS. This outcome is in line with Faqih and Miah (2022). Implementing and applying AI technologies by HR employees that make their work easier and improve their work processes will increase the willingness of the employees to accept such technologies. The boost in AI-influenced talent selection lends strategies, fairness, and performance outcomes to the hands of HR management, and this is a direct consequence of enhanced work (sometimes joy) satisfaction. This implies that AI-enabled talent acquisition is a critical component of the mediation effect that takes the alignment between human-machine interaction and task features to the next level, leading to the satisfaction of HR/talent managers (Faqih & Miah, 2022; Jiang et al., 2023).

HRR significantly and positively mitigates the effect of AITA on HRMS. The results of this study are supported by Sattu et al. (2024). The reason is that when HR departments are adequately prepared and equipped to integrate and leverage AI technologies effectively, the benefits of AI adoption are maximized. HR readiness enhances implementation, facilitates user training, and ensures smooth integration with existing systems. Consequently, HR/talent acquisition managers experience higher satisfaction levels as they perceive AI-enabled solutions as more beneficial and supportive of their organizational goals. Therefore, human resources readiness plays a crucial role in amplifying the positive impact of AI-enabled talent acquisition on managerial satisfaction (Mohapatra et al., 2023).

6. Conclusion and Recommendations

6.1. Summary of the Findings

The findings indicate that several significant aspects greatly influence the adoption and satisfaction with AI-enabled talent acquisition in HR and talent acquisition settings. AITA is enhanced by performance expectancy, which suggests that individuals are more likely to embrace AI technology if they believe that doing so would enhance their work performance and the overall outcomes of the firm. Effort anticipation positively influences AITA, suggesting that users are more likely to embrace AI solutions when they view them as user-friendly and compatible with their existing processes. Additionally, task-technology fit significantly influences AITA, highlighting the importance of aligning AI capabilities with job requirements. However, security and privacy do not significantly impact AITA, suggesting that concerns about data privacy may not significantly deter adoption.

Furthermore, human resources readiness positively moderates the relationship between AITA and HR/TA manager's satisfaction, indicating that organizations with sufficient readiness and perceived cost-effectiveness are more likely to experience higher satisfaction with AI-enabled talent acquisition solutions. The findings underscore the importance of perceived performance benefits, ease of use, task-technology fit, cost-effectiveness, and organizational readiness in shaping attitudes and satisfaction with AI-enabled talent acquisition in HR and TA settings.

6.2. Theoretical Implications/Contribution

This study's utilization of the Unified Theory of Acceptance and Use of Technology (UTAUT) paradigm in AI-enabled talent acquisition in the IT industry offers significant theoretical and practical advancements to the current body of literature on HR and technology adoption. This work contributes to the body of knowledge by presenting empirical evidence on the application of UTAUT in the IT industry. This research examines how UTAUT constructs manifest in a unique socio-cultural and organizational context, enhancing our understanding of technology adoption behaviors in diverse environments. This study enhances the applicability of the Unified Theory of Acceptance and Use of Technology (UTAUT) by examining the contextual elements that can impact the satisfaction of Human Resources/Talent Acquisition (HR/TA) managers with AI-powered talent acquisition. This research contributes to the existing knowledge on technology acceptance (Wongras & Tanantong, 2023). Moreover, the study's findings offer insights into refining and extending the UTAUT framework to accommodate better the nuances and complexities of AI adoption in talent acquisition. By identifying additional factors or modifying existing constructs within the UTAUT model based on empirical evidence from the IT industry, the study contributes to enhancing the predictive power and practical utility of the framework in guiding organizational interventions aimed at promoting AI adoption in HR practices, particularly in Pakistan (Islam et al., 2024).

6.3. Practical Implications/Contribution

Besides, the present study is full of actionable implications for human resource managers, people who handle massive recruitments, and the organizational behavior of the IT industry in Pakistan. First, the data procured emphasizes the quality and quantity of AI systems used in the hiring process and helps the executives ensure the recruitment process is effective with minimal manpower usage. HR and TA specialists would have the opportunity to use the identified factors, including performance expectancy and effort expectation, to develop AI solutions congruent with the organizational goals and particular requirements of the local IT industry in Pakistan.

Also, the research stresses the relevance of HR readiness as a moderator of AI's positive influence on HR/TA managers' feelings about the job. Due to this type of insight, organizational leaders can use them to set initiatives to enhance HR readiness, like training programs, infrastructure development, and change management strategies. The organization could smoothly shift towards AI-empowered talent acquisition by nurturing the readiness mindset and giving HR the tools and abilities required to tackle the challenges. Thus, the overall satisfaction among HR/TA managers could be enhanced.

Furthermore, the research focuses on the considerations for designing a protocol for AI adoption that will counteract the security and privacy threat to talent acquisition. Employees, HR personnel, and TA managers can work closely with IT and cybersecurity departments to implement and maintain the expected cybersecurity policy rules and practice compliance with related regulations. Data security and privacy can help organizations earn the candidates' and stakeholders' trust and support. Consequently, AI-driven recruitment ventures will be more influential and reliable in the Pakistani IT industry.

6.4. Limitations and Future Research Directions

The fact that it has made significant contributions is undeniable. However, this study has some hindrances. The limitations to the transferability of the findings to other parts of the country, specifically in the IT industry, would be to practice more vigilance when generalizing the results to other contexts. In addition, the study solely depends on self-reported data from the HR/TA administrators, which may introduce common method bias and social desirability bias, eventually affecting the data responses. In this regard, the study design fails to provide the causal relation as it is cross-sectional, which instead makes it mandatory to conduct longitudinal research that can explore the prolonged consequences of AI utilization for HR/TA managers' job satisfaction.

Further, future researchers should shed light on these shortcomings and refine AI's knowledge of human capital management in the IT field. The trajectory of AI usage patterns and HR functions can be extensively examined throughout longitudinal studies. Also, comparing AI implementations across different industries and regions could shed some light on the contextual impetus behind the AI implementation and the satisfaction of HR/TA managers. Also, the qualitative studies could help to give a more profound, in-depth understanding of the feelings and perceptions of HR/TA managers about AI talent acquisition aside from the result of the

quantitative methodology of this study. The remedies for the stated gaps and prospects will result in a broader perception of AI achievement within talent acquisition and human resources management work.

References

- Ab Hamid, M., Sami, W., & Sidek, M. (2017). Discriminant validity assessment: Use of Fornell & Larcker criterion versus HTMT criterion. *Journal of Physics: Conference Series*,
- Al-Surmi, A., Bashiri, M., & Koliouis, I. (2022). AI based decision making: combining strategies to improve operational performance. *International Journal of Production Research*, 60(14), 4464-4486.
- Alhassn, I., Asiamah, N., Opuni, F., & Alhassan, A. (2022). The likert scale: exploring the unknowns and their potential to mislead the world. *UDS International Journal of Development*, 9(2), 867-880.
- Ali, S., & Xie, Y. (2021). The impact of Industry 4.0 on organizational performance: the case of Pakistan's retail industry. *European Journal of Management Studies*, 26(2/3), 63-86.
- Allal-Chérif, O., Aránega, A. Y., & Sánchez, R. C. (2021). Intelligent recruitment: How to identify, select, and retain talents from around the world using artificial intelligence. *Technological Forecasting and Social Change*, 169, 120822.
- Batra, S. (2023). Artificial Intelligence (AI) Tools in Talent Acquisition and Its Impact on Hr Effectiveness. *European Economic Letters (EEL)*, 13(4), 267-276.
- Black, J. S., & van Esch, P. (2021). AI-enabled recruiting in the war for talent. *Business Horizons*, 64(4), 513-524.
- Budhwar, P., Malik, A., De Silva, M. T., & Thevisuthan, P. (2022). Artificial intelligence—challenges and opportunities for international HRM: a review and research agenda. *The International Journal of human resource management*, 33(6), 1065-1097.
- Chakraborty, M., & Al Rashdi, S. (2018). Venkatesh et al.'s Unified Theory of Acceptance and Use of Technology (UTAUT)(2003). In *Technology adoption and social issues: Concepts, methodologies, tools, and applications* (pp. 1657-1674). IGI Global.
- Chen, Z. (2023). Collaboration among recruiters and artificial intelligence: removing human prejudices in employment. *Cognition, Technology & Work*, 25(1), 135-149.
- Cheung, G. W., & Wang, C. (2017). Current approaches for assessing convergent and discriminant validity with SEM: Issues and solutions. *Academy of Management Annual Meeting Proceedings*, Briarcliff Manor, NY.
- Chin, W. W. (1998). Commentary: Issues and opinion on structural equation modeling. In (pp. vii-xvi): JSTOR.

- Chiu, Y.-T., Zhu, Y.-Q., & Corbett, J. (2021). In the hearts and minds of employees: A model of pre-adoptive appraisal toward artificial intelligence in organizations. *International Journal of Information Management*, 60, 102379.
- Chowdhury, S., Budhwar, P., Dey, P. K., Joel-Edgar, S., & Abadie, A. (2022). AI-employee collaboration and business performance: Integrating knowledge-based view, socio-technical systems and organisational socialisation framework. *Journal of Business Research*, 144, 31-49.
- Ekka, S., & Singh, P. (2022). Predicting HR professionals' adoption of HR analytics: An extension of Utaut Model. *Organizacija*, 55(1), 77-93.
- Faqihi, A., & Miah, S. J. (2022). Designing an AI-Driven talent intelligence solution: exploring big data to extend the TOE Framework. International Conference on Big Data Intelligence and Computing,
- Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of marketing research*, 18(3), 382-388.
- França, T. J. F., São Mamede, H., Barroso, J. M. P., & Dos Santos, V. M. P. D. (2023). Artificial intelligence applied to potential assessment and talent identification in an organisational context. *Heliyon*, 9(4).
- Grover, K. L. (2022). Artificial Intelligence: A Tool for Optimizing Talent Acquisition. *Issue 2 Int'l JL Mgmt. & Human.*, 5, 460.
- Guarte, J. M., & Barrios, E. B. (2006). Estimation under purposive sampling. *Communications in Statistics-Simulation and Computation*, 35(2), 277-284.
- Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems*, 117(3), 442-458.
- Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011a). PLS-SEM: Indeed a silver bullet. *Journal of Marketing theory and Practice*, 19(2), 139-152.
- Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011b). PLS-SEM: Indeed a silver bullet. *Journal of Marketing theory and Practice*, 19(2), 139-152.
- Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial least squares structural equation modeling: Rigorous applications, better results and higher acceptance. *Long Range Planning*, 46(1-2), 1-12.
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2-24.

- Hair Jr, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis, 1*(2), 107-123.
- Harisha, B., Venkataswamy, K., Devi, R. M., Govindaraj, G. S., & Bhandwalkar, S. S. (2023). The Role Of Artificial Intelligence In Hr: Transforming Recruitment And Hr Operations. *Boletin de Literatura Oral-The Literary Journal, 10*(1), 1374-1384.
- Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: updated guidelines. *Industrial management & data systems, 116*(1), 2-20.
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science, 43*(1), 115-135.
- Holzinger, A., Weippl, E., Tjoa, A. M., & Kieseberg, P. (2021). Digital transformation for sustainable development goals (SDGs)-a security, safety and privacy perspective on AI. International cross-domain conference for machine learning and knowledge extraction,
- Horodyski, P. (2023). Recruiter's perception of artificial intelligence (AI)-based tools in recruitment. *Computers in Human Behavior Reports, 10*, 100298.
- Hussain, A., Akbar, W., & Kumar, R. (2022). Efficient Talent Acquisition: Technology Adaption in Employee Recruitment Process in Pakistan. *Pakistan Business Review*.
- Islam, M., Rahman, M. M., Taher, M. A., Quaosar, G. A. A., & Uddin, M. A. (2024). Using artificial intelligence for hiring talents in a moderated mechanism. *Future Business Journal, 10*(1), 13.
- Jiang, Y., Yang, X., & Zheng, T. (2023). Make chatbots more adaptive: Dual pathways linking human-like cues and tailored response to trust in interactions with chatbots. *Computers in Human Behavior, 138*, 107485.
- Kambur, E., & Akar, C. (2022). Human resource developments with the touch of artificial intelligence: a scale development study. *International Journal of Manpower, 43*(1), 168-205.
- Kaur, M., & Gandolfi, F. (2023). Artificial Intelligence in Human Resource Management- Challenges and Future Research Recommendations. *Revista de Management Comparat International, 24*(3), 382-393.
- Lin, S., Döngül, E. S., Uygun, S. V., Öztürk, M. B., Huy, D. T. N., & Tuan, P. V. (2022). Exploring the relationship between abusive management, self-efficacy and organizational performance in the context of human-machine interaction technology and artificial intelligence with the effect of ergonomics. *Sustainability, 14*(4), 1949.

- Malik, A., Budhwar, P., Patel, C., & Srikanth, N. (2022). May the bots be with you! Delivering HR cost-effectiveness and individualised employee experiences in an MNE. *The International Journal of human resource management*, 33(6), 1148-1178.
- Mohapatra, L. M., Kamesh, A., & Roul, J. (2023). Challenges and Path Ahead for Artificial Intelligence-aided Human Resource Management. In *The Adoption and Effect of Artificial Intelligence on Human Resources Management, Part A* (pp. 107-121). Emerald Publishing Limited.
- Morgan, G. A., & Harmon, R. J. (2001). Data collection techniques. *Journal-American Academy Of Child And Adolescent Psychiatry*, 40(8), 973-976.
- Murdoch, B. (2021). Privacy and artificial intelligence: challenges for protecting health information in a new era. *BMC Medical Ethics*, 22, 1-5.
- Ning, Y., Li, L., Xu, S. X., & Yang, S. (2023). How do digital technologies improve supply chain resilience in the COVID-19 pandemic? Evidence from Chinese manufacturing firms. *Frontiers of Engineering Management*, 10(1), 39-50.
- Ore, O., & Sposato, M. (2022). Opportunities and risks of artificial intelligence in recruitment and selection. *International Journal of Organizational Analysis*, 30(6), 1771-1782.
- Pillai, R., & Sivathanu, B. (2020). Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organizations. *Benchmarking: An International Journal*, 27(9), 2599-2629.
- Rahi, S., Othman Mansour, M. M., Alghizzawi, M., & Alnaser, F. M. (2019). Integration of UTAUT model in internet banking adoption context: The mediating role of performance expectancy and effort expectancy. *Journal of Research in Interactive Marketing*, 13(3), 411-435.
- Rai, N., & Thapa, B. (2015). A study on purposive sampling method in research. *Kathmandu: Kathmandu School of Law*, 5(1), 8-15.
- Russo, G. M., Tomei, P. A., Serra, B., & Mello, S. (2021). Differences in the use of 5-or 7-point likert scale: an application in food safety culture. *Organizational Cultures*, 21(2), 1.
- Sattu, R., Das, S., & Jena, L. K. (2024). Should I adopt AI during talent acquisition? Evidence from HR professionals of Indian IT organisations. *Journal of Organizational Effectiveness: People and Performance*.
- Shahzad, M. F., Xu, S., Naveed, W., Nusrat, S., & Zahid, I. (2023). Investigating the impact of artificial intelligence on human resource functions in the health sector of China: A mediated moderation model. *Heliyon*, 9(11).

- Shakeel, A., & Siddiqui, D. A. (2021). The effect of Technological, Organizational, Environmental, and Task Technology fit on the Adoption and usage of artificial intelligence (AI) for talent acquisition (TA): Evidence from the Pakistani banking sector. *Organizational, Environmental, and Task Technology fit on the Adoption and usage of artificial intelligence (AI) for talent acquisition (TA): Evidence from the Pakistani banking sector.*(October 15, 2021).
- Tanantong, T., & Wongras, P. (2024). A UTAUT-Based Framework for Analyzing Users' Intention to Adopt Artificial Intelligence in Human Resource Recruitment: A Case Study of Thailand. *Systems, 12*(1), 28.
- Vedapradha, R., Hariharan, R., Praveenraj, D. D. W., Sudha, E., & Ashok, J. (2023). Talent acquisition-artificial intelligence to manage recruitment. *E3S Web of Conferences,*
- Vendramin, N., Nardelli, G., & Ipsen, C. (2021). Task-Technology Fit Theory: An approach for mitigating technostress. In *A Handbook of Theories on Designing Alignment between People and the Office Environment* (pp. 39-53). Routledge.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly, 425-478.*
- Wongras, P., & Tanantong, T. (2023). An Extended UTAUT Model for Analyzing Users' Acceptance Factors for Artificial Intelligence Adoption in Human Resource Recruitment: A Case Study of Thailand.