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Artificial Intelligence (Ai) For Talent Acquisition (Ta) In The Manufacturing Sector Of Pakistan

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Abstract

The study examined the adoption of AI-enabled talent acquisition towards HR or talent acquisition manager satisfaction in the manufacturing sector of Pakistan based on the decision-maker technology-organization-environment (D-TOE) framework. 219 responses have been collected from the HR and talent acquisition managers of manufacturing firms in Karachi using a nonprobability purposive sampling technique, and a five-point Likert scale questionnaire has been used for data collection. The study has employed the PLS-SEM technique for data analysis using SmartPLS v4. The results showed that the adoption of AI-enabled talent acquisition has a positive effect on HR/TA manager's satisfaction; in addition, cost-effectiveness, relative advantage, top management support, competitive pressure, and support from AI vendors have a positive effect on the adoption of AI-enabled talent acquisition whereas orientation towards AI adoption has weak positive effect on adoption of AI-enabled talent acquisition. However, security and privacy concerns, HR readiness, and task-technology fit do not affect adopting AI-enabled talent acquisition. Moreover, adopting AI-enabled talent acquisition positively mediates between all exogenous constructs and HR/TA manager's satisfaction except security and privacy concerns, HR readiness, and task-technology fit. HR managers must also consider the AI technology's compatibility and suitability for TA functions according to the organization's requirements when acquiring AIT for TA.

Keywords: Artificial Intelligence (AI), Talent Acquisition (TA), D-TOE Framework, Pakistan, PLS-SEM.

1. Introduction

Xin et al. (2022) stated that technology is a critical component of modern business growth in the era of globalization. Local companies no longer compete with one another within the country but instead are continuously competing on a global scale, which is challenging how business is conducted. Organizations must utilize technology to maintain a competitive advantage in the global business environment. Organizations are using artificial intelligence (AI) at a rapid pace. AI use has increased firm returns and even reduced costs. AI is a collection of techniques that enables computers to carry out activities that do not require the analytical abilities that human intelligence provides (Xin et al., 2022).

Moreover, AI reduces manual analysis and provides recommendations based on facts rather than human emotion, eliminating biased decisions and assisting HR professionals in taking effective measures. It is also crucial for any firm to anticipate the best possible hiring. The talent acquisition (TA) process supported by an AI-based system will help a firm publish open positions on its website or portal, conduct preliminary candidate screening, schedule interviews, evaluate, prepare for, and generate new hire data (Oswal et al., 2020). Using AI in the TA process will increase efficiency and timeliness and save hiring costs by streamlining the hiring process. Additionally, AI can assist HR managers in creating a website that attracts applicants since the hiring messaging may be customized to target people with particular skill sets (Xin et al., 2022).

Incorporating AI into talent management procedures is not a simple plug-and-play process. It necessitates thoroughly assessing substantial risks and difficulties that companies must handle (Budhwar et al., 2022). They must specifically address problems with the lack of trust in AI decision-making, possible biases, ethical issues, and legal risks. The considerable amount of data utilized for AI is yet another major challenge. This must be kept secret and private since it contains essential employee personal information (Varghese, 2023). The major obstacles to adopting AI in firms include a lack of expertise, initial financial and time commitments, infrastructure, resources, experience, and corporate size. Additionally, inadequate physical and technological infrastructure, a lack of qualified individuals, and a lack of data availability are significant hurdles in acquiring and implementing AI (Bhalerao et al., 2022).

Batra (2023) indicated that another significant obstacle to the deployment of AI is the lack of pertinent data. The adoption of AI-enabled TA is hindered by the firm's weak financial condition, a lack of knowledge of the benefits of AI, and a scarcity of educated or proficient human resources. Likewise, the adoption of AI in manufacturing firms is hindered by other critical factors like employee skill levels and the availability of high-quality data, which reduce HR managers' satisfaction because firms do not fully understand the importance of AI technologies. Size and an entrepreneurial mindset are also obstacles to AI implementation in firms (Bhalerao et al., 2022).

First, earlier research has assessed team and individual performance measures, including sales targets, project results, and customer satisfaction ratings, which might provide insights into how talent acquisition strategies affect overall organizational performance (Subashini & Velmurugan, 2023). However, it has also been noted that talent technology and workforce analytics are crucial for increasing the efficacy of TA strategies and increasing HR managers' level of satisfaction. There are still research gaps about these strategies' long-term effects, particular processes, and contextual applicability. More research is required to examine the relationship between talent acquisition strategies and organizational outcomes in various industries and contexts (Al-Alawi et al., 2021).

Second, the use of AI for hiring at the organizational level has been the subject of several research. There is a paucity of studies on the use of AI technology in firms for TA roles. Implementing AI for TA will help HR managers improve the performance of the HR department and TA role (Mehrotra & Khanna, 2022). Lastly, there is a lack of a theoretical framework for using AI for TA in previous studies. However, the TOE framework was utilized in this study. This framework will provide a perceptive and thorough emphasis to forecast the organization-level adoption of AI technology for TA functions (Pillai & Sivathanu, 2020). Therefore, the study aims to investigate factors affecting HR/TA managers' satisfaction and the adoption of AI-enabled TA. The study also examined how task technology fit and orientation toward AI adoption influenced the adoption of AI-enabled TA, revealing that AI has a huge potential to increase efficiency and effectiveness in the talent acquisition process.

The remainder of the paper consisted of theoretical underpinnings, development of the hypothesis, and research framework, followed by a discussion of the sample population, measures, data collection method, and data analysis technique. The fourth section discusses the study findings and supportive arguments from past studies. The last section discusses conclusive remarks, theoretical and practical implications, limitations, and future research directions.

2. Literature Review

2.1. Decision-Maker Technology-Organization-Environment (D-TOE) Framework

Tornatzky Fleischer (1990) developed the TOE framework. TOE model uses three group perspectives—technological, organizational, and environmental—to describe how technology adoption variables affect the organization inside and outside. (Pillai & Sivathanu, 2020). According to the TOE model, the organizational perspective emphasizes factors such as firm size, formalization and centralization of the organization, the complexity of organizational structure, top management support, and organizational readiness. In contrast, the technology perspective emphasizes the technological resources required for an organization to adopt new technology (Matandela, 2017).

Additionally, TOE emphasized that firms must monitor, assess, and respond to external changes while modifying their internal resources as needed. From the environmental perspective, the TOE model considers an organization's competitors, governmental laws and rules, industry support, and supplier relationships (Pillai & Sivathanu, 2020).

2.2. Adoption of AI-enabled talent acquisition and HR/TA managers' satisfaction

Pillai and Sivathanu (2020) found that TA is a key sign of a company's success in this competitive, global marketplace. Organizations are competing with one another for the best talent because everyone believes that a talented workforce improves organizational performance. Organizational TA roles are changing due to AI technology (Jose, 2019). Subashini and Velmurugan (2023) also indicated that AI for TA improves applicant diversity, selection rate, and experience throughout the selection process. AI technology helps HR managers in enhancing TA operations. Therefore, the study has proposed the following hypothesis:

H1. Adoption of AI-enabled TA has a significant effect on HR/TA manager's satisfaction.

2.3. Relationship between cost-effectiveness, adoption of AI-enabled TA and HR/TA managers' satisfaction

Pillai and Sivathanu (2020) argued that the organization must invest in AI technology for TA, which means costs must be invested for its acquisition. Cost is measured as cost-effectiveness (COS), which indicates that the advantages of adopting new technologies outweigh their costs. Organizations take advantage of adopting new technologies to reduce costs (Malik et al., 2022). AIT avoids repetitive tasks like collecting and shortlisting resumes from websites and conducting the initial interview, which saves time and cost associated with the TA process. Understanding the impact of COS on ADP of AI-enabled TA is essential since it saves money while providing faster and more accurate results.

Budhwar et al. (2022) also said that AI-enabled recruiting and selection play a significant part in selecting the most suitable employees for firms since these innovative technologies have the potential to process vast amounts of data more quickly than humans can (Li et al., 2021).

Therefore, the study has proposed the following hypotheses:

H2. Cost-effectiveness has a significant effect on the adoption of AI-enabled TA.

H3. Adoption of AI-enabled TA significantly mediates the effect of cost-effectiveness on HR/TA manager's satisfaction.

2.4. Relationship between relative advantage, adoption of AI-enabled TA and HR/TA managers' satisfaction

Siripipatthanakul et al. (2022) explained that relative advantage (REA) measures how much an invention is considered superior to the concept it replaces. If a new technology provides a comparative advantage over the organization's existing methods or technology, it is more likely to be implemented. Pillai and Sivathanu (2020) said that HR managers can find and hire people more quickly due to AI technology than they could before. AIT helps HR managers improve hiring outcomes, which enhances the requirement for understanding the relationship between REA and ADP of AI-enabled TA.

Votto et al. (2021) also said that HR managers may speed up the recruiting process and ensure a more accurate applicant selection using AI-powered platforms. AI-enabled TA may also assist HR managers in rapidly assessing and ranking internal and external applicants according to their skills and capabilities (Arora et al., 2023). Therefore, the study has proposed the following hypotheses:

H4. Relative advantage has a significant effect on the adoption of AI-enabled TA.

H5. Adoption of AI-enabled TA significantly mediates the effect of relative advantage on HR/TA manager's satisfaction.

2.5. Relationship between security/privacy concerns, adoption of AI-enabled TA and HR/TA managers' satisfaction

Security and privacy (SNP) refers to the degree to which technology and information systems are considered insecure for carrying out activities and exchanging data. AI technology (AIT) for TA contains bulk data on hiring, including candidate profiles, CVs, and selection outcomes. AIT must be sufficiently secure to handle such data to protect personal information and maintain the confidentiality of selection results (Pillai & Sivathanu, 2020). Additionally, the use of AI for TA has given rise to possible security, legal, moral, and ethical issues, as well as privacy concerns for potential candidates. HR managers are concerned about the SNP of applicant and employee data while using AIT for TA (Pandita & Yadav, 2022). Okeyika et al. (2023) also found that AI increases HR managers' satisfaction by improving decision-making with valuable insights from HR and predictive analytics. AI, for instance, can increase recruiting efficiency by automating the selection and screening process (Saha et al., 2023). Therefore, the study has proposed the following hypotheses:

H6. Security and privacy concerns have a significant effect on the adoption of AI-enabled TA.

H7. Adoption of AI-enabled TA significantly mediates the effect of security and privacy concerns on HR/TA managers' satisfaction.

2.6. Relationship between HR readiness, adoption of AI-enabled TA and HR/TA managers' satisfaction

Pillai and Sivathanu (2020) indicated that HR technology adoption depends on HR readiness (HRR). Even if individuals enjoy technology, they will not embrace it if they lack the necessary resources or expertise. The HR department would extensively utilize AIT; therefore, AIT for TA adoption requires that the HR budget, resources, and skill set be in place. Although HR managers are experimenting with new technology, they still mostly rely on traditional hiring practices (Bhagyalakshmi & Maria, 2021). As a result, HR readiness is crucial for adopting AI-enabled TA. AI will also be able to help HR managers identify possible retention risks and prevent top employees from leaving the organization (Gupta, 2022). Therefore, the study has proposed the following hypotheses:

H8. HR readiness has a significant effect on the adoption of AI-enabled TA.

H9. Adoption of AI-enabled TA significantly mediates the effect of HR readiness on HR/TA manager satisfaction.

2.7. Relationship between top management support, adoption of AI-enabled TA and HR/TA managers' satisfaction

Top management is essential in technology adoption since they actively support introducing new technology. Top management will investigate the specifics of AIT before adoption because it will help in the organization's personnel selection. Since the top management provides the funding for the new technology, it has to be persuaded to support AIT for TA (Pillai & Sivathanu, 2020).

Subashini and Velmurugan (2023) also identified that AI makes it possible to gather and analyze data in HR operations to remove biases and ensure they are selecting the best candidates or providing the benefits package. Oueidat (2022) said that AI may automate tiresome administrative tasks, freeing HR managers to concentrate on other aspects of their jobs. This can increase the efficiency and satisfaction of HR managers and give them more time to work on activities that need their expertise (Kolbjørnsrud et al., 2016). Therefore, the study has proposed the following hypotheses:

H10. Top management support has a significant effect on the adoption of AI-enabled TA.

H11. Adoption of AI-enabled TA significantly mediates the effect of top management support on HR/TA manager's satisfaction.

2.8. Relationship between competitive pressure, adoption of AI-enabled TA and HR/TA managers' satisfaction

Pillai and Sivathanu (2020) said the external environment influences organizational technology decisions. Competitive pressure (COM) describes the pressure an organization feels to adopt a technology as a result of general industry competition and operating procedures in order to survive in the market. COM compels firms to use information system (IS) innovation and HR technology (Subashini & Velmurugan, 2023). TA is a crucial and challenging role for managers. HR managers must always look for new TA techniques being deployed by other companies. HR managers may use AIT for TA to find talent. Many firms are gradually adopting various types of AI technology for TA operations to survive and compete in the competitive market (Guenole & Feinzig, 2018).

Additionally, TA is crucial for the growth of the firm. AI-enabled TA provides the right processes and tools to help and empower managers. AIT also allows managers to improve their knowledge and abilities, giving the business a competitive edge, enhancing performance, and increasing HR managers' satisfaction (Srivastava & Bhatnagar, 2010). Therefore, the study has proposed the following hypotheses:

H12. Competitive pressure has a significant effect on the adoption of AI-enabled TA.

H13. Adoption of AI-enabled TA significantly mediates the effect of competitive pressure on HR/TA manager's satisfaction.

2.9. Relationship between support from AI vendor, adoption of AI-enabled TA and HR/TA managers' satisfaction

Vendor support refers to the assistance technology suppliers provide for the application and utilization of technological advancements. It is required for the constant problem-solving of any new technological deployment. Vendor support is one of the critical indicators of how new technologies will be adopted (Pillai & Sivathanu, 2020). HR managers lack the expertise needed to use AIT and conduct talent acquisition. The vendor must develop different AI software functions and adapt them to the organization's requirements for talent acquisition. It implies that vendor assistance will be required to deploy AI for TA (Imron et al., 2019).

Additionally, managers and employees often lack knowledge of new technologies; as a result, they require help and training from technology vendors, which might influence their decision to use AI technology for TA (Pillai et al., 2022). Chugunova and Danilov (2023) also indicated that HR managers may utilize AIT to improve the application process by creating forms that are simpler to use and thereby lessen the number of abandoned applications with the help of the vendor. HR should adopt a more holistic approach to personnel management to guarantee the long-term success of an organization (Siripipatthanakul et al., 2022). Therefore, the study has proposed the following hypotheses:

H14. Support from AI vendor has a significant effect on the adoption of AI-enabled TA.

H15. Adoption of AI-enabled TA significantly mediates the effect of support from AI vendors on HR/TA manager's satisfaction.

2.10. Relationship between orientation towards AI adoption, adoption of AI-enabled TA and HR/TA managers' satisfaction

Adoption may refer to the selection of new technology by an organization to meet its requirements. Adoption does not always imply usage of the new technology, even when companies have decided to employ it and have allocated the necessary resources for its acquisition (Pillai & Sivathanu, 2020). Bhalerao et al. (2022) also said that AIT will carry out TA tasks and improve TA by saving money and time. HR managers would thus keep utilizing it. Due to the advantages of AIT that HR managers may use, its adoption for TA may impact how it is used to carry out TA responsibilities (George & Thomas, 2019). Additionally, managers will benefit from using AIT by enhancing the performance of the HR department and TA role. (Budhwar et al., 2022). Therefore, the study has proposed the following hypotheses:

H16. Orientation towards AI adoption has a significant effect on the adoption of AI-enabled TA.

H17. Adopting AI-enabled TA significantly mediates the effect of orientation toward AI adoption on HR/TA managers' satisfaction.

2.11. Relationship between task-technology fit, adoption of AI-enabled TA and HR/TA managers' satisfaction

Technology-task fit (TTF) refers to the level of technical assistance that the information system gives an individual to carry out his or her task portfolio. TTF is influenced by technological factors (Pillai & Sivathanu, 2020). AIT possesses the necessary qualities for performing TA tasks, but the technology must be suitable for the organization's TA operations. HR managers must carry out the responsibilities of TA, which include recruiting, screening, and shortlisting individuals before performing the selection process (Ramesh & Das, 2022). Gupta (2022) also indicated that AI technology can perform these TA responsibilities to company requirements. As a result, HR managers are depending more on AIT for TA. TTF also emphasizes that technology will be employed when it enhances employee performance to the point that it is necessary for the work. Faqihi and Miah (2023) also revealed that AIT handles the monotonous tasks associated with hiring, accurately optimizes the process, and increases HR managers' satisfaction. If AIT effectively handles the various TA functions, this might result in frequent use of AIT for TA (Bhagyalakshmi & Maria, 2021). Therefore, the study has proposed the following hypotheses:

- H18. Task-technology fit has a significant effect on the adoption of AI-enabled TA.
- H19. Adoption of AI-enabled TA significantly mediates the effect of task-technology fit on HR/TA manager's satisfaction.

2.12. Research framework

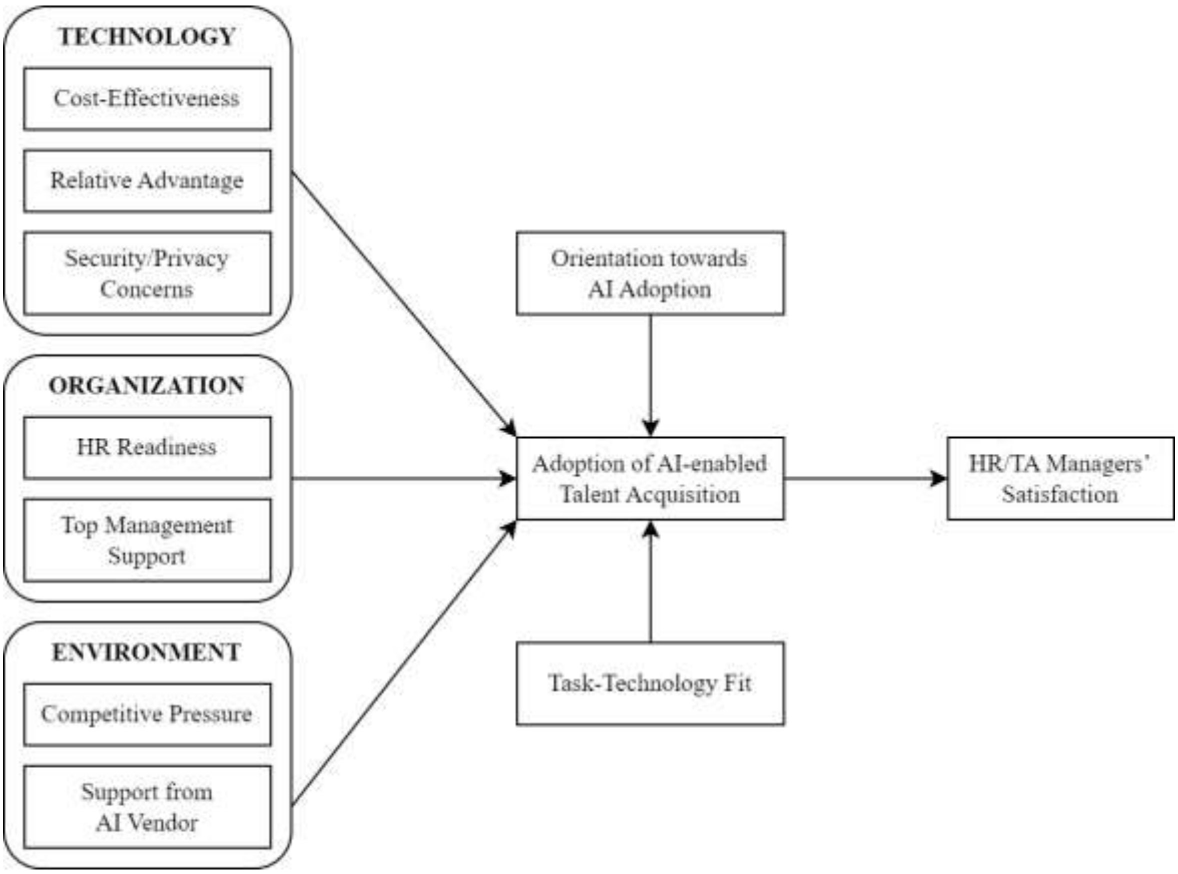

Figure 2.1: Research Model

3. Methodology

3.1. Sample and population

Bakar (2019) said that the manufacturing sector is quite essential for every country. Pakistan's manufacturing sector is dispersed throughout the country, with some regions dominating particular manufacturing industries. Pakistan's manufacturing sector contributes 12.79 percent of the country's GDP and employs 16.1 percent of the workforce. AI has the potential to change the manufacturing sector completely. AI may generate data to improve failure prediction and maintenance planning. Maintenance expenses for production lines are thereby decreased (Oueidat, 2022). AI-driven automation also allows manufacturing firm's employees to spend less time on repetitive tasks and more time on creative aspects of their work.

Additionally, a robust manufacturing sector promotes domestic production, exports, and employment, which enhances an economy's overall growth (Saßmannshausen et al., 2021). Therefore, the study has chosen HR and talent acquisition managers of manufacturing firms in Karachi as a sample population. Respondents' profiles are provided in table 3.1.

Table 3.1: Demographic Profile (n = 219)

		N	%
Age	25-30 years	53	24.2
	30-35 years	42	19.2
	35-40 years	54	24.7
	40 above	70	32.0
Gender	Male	124	56.6
	Female	95	43.4
Education	Undergraduate	64	29.2
	Graduate	77	35.2
	Postgraduate	78	35.6
Designation	Assistant Manager	57	26.0
	Manager	56	25.6
	Deputy Manager	48	21.9
	Senior Manager	58	26.5
Experience	Less than 3 years	45	20.5
	3 to 5 years	50	22.8
	6 to 9 years	61	27.9
	10 and above	63	28.8
Familiarity with AI in TA	Very Familiar	59	26.9
	Neutral	48	21.9
	Somewhat Unfamiliar	59	26.9
	Very Unfamiliar	53	24.2

3.2. Measures

3.2.1. Cost-effectiveness

Cost-effectiveness is a metric that evaluates the efficiency of resource allocation in attaining a specific end or result. It involves comparing the expenses invested against the benefits or results received (Matta et al., 2022). The study has adapted five measures from Trang (2022) based on a five-point Likert scale, for example, “I think the annual/monthly fee is reasonable.” with an alpha coefficient of 0.781.

3.2.2. Relative advantage

The term "relative advantage" is often used in innovation and technology adoption to describe how people or organizations see a new technology, service, or product as superior to existing ones (Park et al., 2022). The study has adapted three measures from Flight et al. (2011) based on a five-point Likert scale, for example “I think AI is more comfortable to use than others that meet similar needs.” with an alpha coefficient of 0.70 and the study has adapted two measures from Hmoud et al. (2023) based on five-point Likert scale, for example “I believe that AI system could enhance the efficiency of my industry.” with an alpha coefficient of 0.810.

3.2.3. Security/privacy concerns

The dangers and problems that might arise from protecting private information, assets, systems, and sensitive data from unauthorized access, disclosure, change, or destruction are security and privacy concerns (Kafi & Akter, 2023). The study has adopted seven measures from Xu and Teo (2004) based on a five-point Likert scale, such as “I am concerned that the service providers may keep private location information in a non-secure manner.” with an alpha coefficient of 0.902.

3.2.4. HR readiness

The ability of an organization’s HR department to successfully handle and support the business’s operational and strategic requirements is referred to as HR Readiness (Syamsuri et al., 2022). The study has adapted four measures from Duang-Ek-Anong et al. (2019) based on a five-point Likert scale, such as “I am confident in my ability to adapt to AI-driven talent acquisition processes.” with an alpha coefficient of 0.869.

3.2.5. Top management support

The term "top management support" describes the complete encouragement, dedication, and participation of an organization's highest-ranking executives, such as the CEO, board of directors, and other senior leaders, in achieving a set of predetermined objectives (Mamo, 2023). The study has adopted six measures from Al-Omoush (2021) based on a five-point Likert scale, for example, “My managers have extensive knowledge of AI capabilities.” with an alpha coefficient of 0.834.

3.2.6. Competitive pressure

The term “competitive pressure” describes the power or influence applied to companies, sectors of the economy, or people working in a market or other competitive environment (Marco-Lajara et al., 2022). The study has adopted three measures from Jia et al. (2017) based on a five-point Likert scale, such as “My choice to adopt AI systems would be strongly influenced by what competitors in the industry are doing.” Two measures from (Hmoud et al., 2023) are based on a five-point Likert scale, for example, “More and more competitors in my industry have conducted team collaboration and communication.” with an alpha coefficient of 0.840.

3.2.7. Support from AI vendor

Support from an AI vendor encompasses a wide array of services and helps the vendor provide to their customers to guarantee the practical implementation, functioning, and upkeep of AI solutions and goods (Hmoud et al., 2023). The study has adapted four measures from Hmoud et al. (2023) based on a five-point Likert scale, such as “Technology vendors actively market AI adoption.” with an alpha coefficient of 0.704.

3.2.8. Orientation towards AI adoption

Orientation toward AI adoption describes a company's strategic posture, philosophy, and approach toward adopting AI technology for use in the company's operations, goods, or services (Upadhyay et al., 2023). The study has adapted four measures from Lada et al. (2023) based on a seven-point Likert scale, such as "I believe that integrating AI into our talent acquisition processes could enhance our efficiency and effectiveness." with an alpha coefficient of 0.993.

3.2.9. Adoption of AI-enabled talent acquisition

The strategic integration and use of AI tools and technology into an organization's recruiting and human resources procedures is AI-enabled talent acquisition (Gupta, 2022). The study has adapted three measures from Adnan et al. (2020) based on a five-point Likert scale, for example, "I believe that AI-enabled systems revolutionize talent acquisition in the manufacturing sector. "

3.2.10. Task-technology fit

Task-technology fit is an idea from the fields of information systems and technology management that evaluates how well a task or set of tasks within an organization fits with the technology or digital tools that are used to support those tasks (Muchenje & Seppänen, 2023). The study has adapted five measures from Zhao et al. (2023) based on a five-point Likert scale, such as "I find it easy to integrate AI-driven solutions into our talent acquisition processes." with an alpha coefficient of 0.888.

3.2.11. HR/TA manager's satisfaction

HR/TA manager's satisfaction is the degree of satisfaction, fulfillment, and a positive feeling that a person who holds the position of HR or TA manager in an organization experiences (Kerhoas, 2023). The study has adapted three measures from Chen et al. (2022) based on a five-point Likert scale, such as "My satisfaction with using AI in business operations has increased." The study has adapted two measures from Khilji (2004) based on a five-point Likert scale, for example, "Through compensation practices, I am satisfied with AI adoption."

3.3. Data collection

The survey method refers to gathering data from a sample using responses provided by respondents to questions or statements (Fitri et al., 2022). The study used the survey approach since it effectively defines the characteristics of a sizable population, assuring a more accurate sample to acquire particular information from which to draw conclusions and make essential judgments (You et al., 2022). It also provides a simple analysis and visualization of the data. This method has the benefit of an easy analytical procedure, allowing for immediate visualization of the results. Wijaya et al. (2021) stated that surveys are an excellent tool for quantitative study since they are adaptable, affordable, and allow for data collection from a vast sample size.

3.4. Data analysis

Hair et al. (2017) said that PLS-SEM analyzes how well the model accounts for the target constructs of interest and estimates the relationship between the latent variables. PLS-SEM's flexible data requirements allow it to estimate highly complex models. It is better for investigating and predicting with categorical or ordinal data, complex models with many variables and indicators, higher-order constructs, formative assessment, and mediation and moderation effects (Hair et al., 2019). PLS-SEM enables researchers to develop and assess complex cause-effect models utilizing latent and observed variables. Additionally, it predicts the variables' outcomes accurately and assesses their predictive power by taking into account a number of variables (Hair Jr et al., 2017). Therefore, the current study has utilized PLS-SEM for data analysis. The objective of using this technique was to examine a small sample size while producing effective and significant results.

4. Results and Discussions

4.1. Measurement model

The outcomes of the measurement model utilizing the PLS algorithm approach are shown in Table 4.1 below.

Table 4.1: Measurement Model

	Loadings	Prob.	CR	AVE
ATA1 <- ATA	0.795	0.000	0.818	0.693
ATA3 <- ATA	0.869	0.000		
CE2 <- CE	0.933	0.000	0.942	0.890
CE4 <- CE	0.954	0.000		
CP1 <- CP	0.686	0.001	0.911	0.721
CP2 <- CP	0.886	0.000		
CP3 <- CP	0.879	0.000		

CP4 <- CP	0.924	0.000		
HMS1 <- HMS	0.749	0.000	0.907	0.709
HMS2 <- HMS	0.841	0.000		
HMS3 <- HMS	0.899	0.000		
HMS4 <- HMS	0.873	0.000		
HR3 <- HR	0.942	0.000	0.938	0.884
HR4 <- HR	0.938	0.000		
OAA1 <- OAA	0.853	0.000	0.897	0.687
OAA2 <- OAA	0.767	0.000		
OAA3 <- OAA	0.916	0.000		
OAA4 <- OAA	0.770	0.000		
RA1 <- RA	0.825	0.000	0.886	0.663
RA2 <- RA	0.908	0.000		
RA3 <- RA	0.872	0.000		
RA4 <- RA	0.622	0.000		
SAV1 <- SAV	0.857	0.000	0.911	0.720
SAV2 <- SAV	0.853	0.000		
SAV3 <- SAV	0.772	0.000		
SAV4 <- SAV	0.907	0.000		
SPC5 <- SPC	0.681	0.019	0.778	0.557
SPC6 <- SPC	0.504	0.135		
SPC7 <- SPC	0.976	0.013		
TMS1 <- TMS	0.898	0.000	0.850	0.597
TMS2 <- TMS	0.633	0.000		
TMS3 <- TMS	0.927	0.000		
TMS4 <- TMS	0.567	0.000		
TTF3 <- TTF	0.940	0.000	0.952	0.868
TTF4 <- TTF	0.887	0.000		
TTF5 <- TTF	0.965	0.000		

Here, all the outer loadings are more significant than 0.5. In structural equation modeling (SEM), this is a good indicator. It suggests that each indicator accurately represents the corresponding underlying component. Hair et al. (2011); Hair et al. (2019) recommended that average variance extracted (AVE) and composite reliability (CR) be more significant than 0.50 and 0.70, respectively, and that outer loadings need to be greater than 0.70. Indicators with loadings greater than 0.50, with probability levels below 5%, are likewise displayed in the above table (Hair et al., 2011).

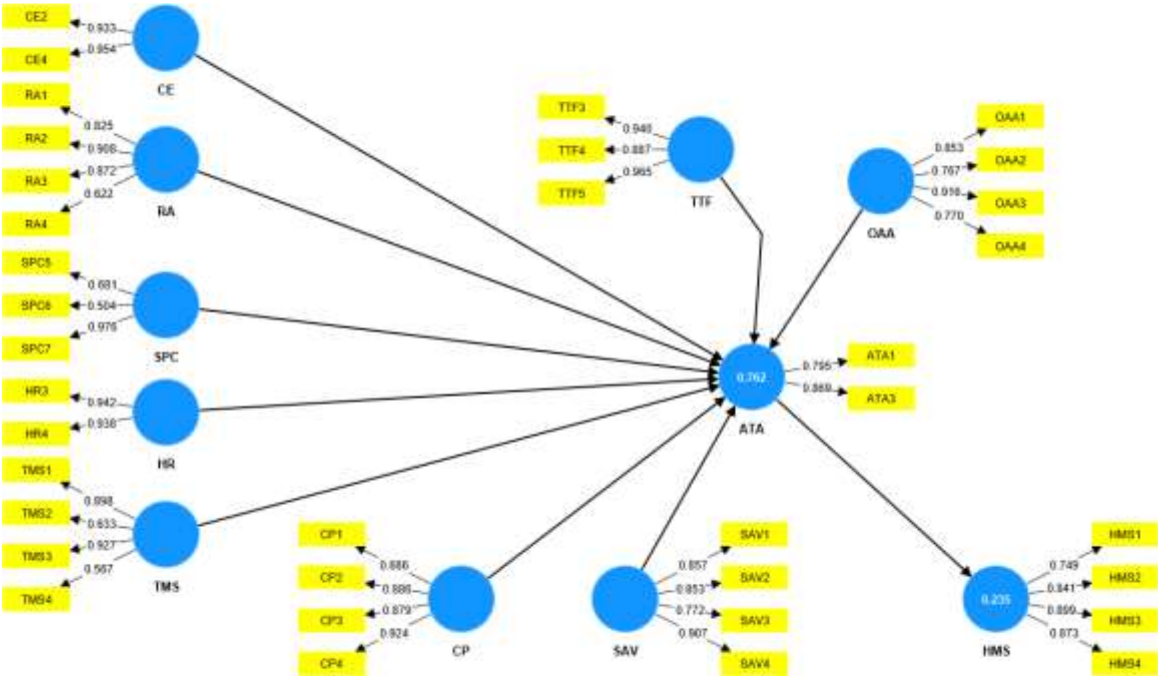

Figure 4.1: PLS Algorithm

4.2. Discriminant validity

The results of the HTMT ratio for the PLS algorithm's assessment of discriminant validity are displayed in Table 4.2.

Table 4.2: HTMT Ratio

	ATA	CE	CP	HMS	HR	OAA	RA	SAV	SPC	TMS	TTF
ATA											
CE	0.979										
CP	0.254	0.415									
HMS	0.671	0.275	0.228								
HR	0.834	0.616	0.404	0.237							
OAA	0.853	0.752	0.232	0.478	0.551						
RA	0.826	0.801	0.765	0.456	0.764	0.852					
SAV	0.364	0.322	0.432	0.213	0.271	0.411	0.321				
SPC	0.074	0.047	0.057	0.063	0.155	0.050	0.079	0.099			
TMS	0.816	0.524	0.484	0.467	0.769	0.377	0.627	0.248	0.063		
TTF	0.848	0.774	0.455	0.521	0.841	0.673	0.813	0.339	0.097	0.725	

Above table has shown that all the constructs have HTMT ratio below the recommended threshold of 0.90 (Henseler et al., 2016; Henseler et al., 2015) except the HTMT ratio between CE and ATA found 0.979. In this regard, Hair et al. (2019) suggested that HTMT ratio should be significantly different from 1.00 using the bootstrapping technique. Therefore, the above table manifested that all the constructs have established discriminant validity using HTMT ratio.

4.3. Structural model

The outcome of the hypothesis testing for the direct-effect analysis with PLS route modeling is shown in Table 4.3 below.

Table 4.3: Direct-Effect Analysis

	Estimate	S. D.	t-Stats	Prob.	Decision
ATA -> HMS	0.485	0.053	9.075	0.000	Accepted
CE -> ATA	0.506	0.132	3.838	0.000	Accepted
CP -> ATA	0.518	0.145	3.561	0.000	Accepted
HR -> ATA	0.025	0.126	0.198	0.843	Rejected
OAA -> ATA	0.231	0.128	1.809	0.071	Accepted
RA -> ATA	0.654	0.167	3.905	0.000	Accepted
SAV -> ATA	0.215	0.094	2.293	0.022	Accepted
SPC -> ATA	0.026	0.043	0.589	0.556	Rejected
TMS -> ATA	0.399	0.080	4.964	0.000	Accepted
TTF -> ATA	0.159	0.103	1.552	0.121	Rejected

The above table has shown that ATA (ß = 0.485, $p < 0.05$) has a positively significant effect on HMS. CE (ß = 0.506, $p < 0.05$) has a positively significant effect on ATA. CP (ß = 0.518, $p < 0.05$) has a positively significant effect on ATA. The above table has shown that HR (ß = 0.025, $p > 0.05$) has a positively insignificant effect on ATA. OAA (ß = 0.231, $p < 0.05$) has a positive and significant effect on ATA. RA (ß = 0.654, $p < 0.05$) has a positive and significant effect on ATA. SAV (ß = 0.215, $p < 0.05$) has a positively significant effect on ATA. SPC (ß = 0.026, $p > 0.05$) has a positively insignificant effect on ATA. TMS (ß = 0.399, $p < 0.05$) has a positive and significant effect on ATA. TTF (ß = 0.159, $p > 0.05$) has a positively insignificant effect on ATA.

The outcomes of the indirect-effect analysis for hypothesis testing using PLS bootstrapping are displayed in Table 4.4.

Table 4.4: Specific Indirect-Effect Analysis

	Estimate	S. D.	t-Stats	Prob.	Prob.
CP -> ATA -> HMS	0.251	0.075	3.336	0.001	Accepted
RA -> ATA -> HMS	0.317	0.088	3.592	0.000	Accepted
TTF -> ATA -> HMS	0.077	0.052	1.489	0.137	Rejected
SPC -> ATA -> HMS	0.012	0.021	0.581	0.561	Rejected
TMS -> ATA -> HMS	0.193	0.044	4.437	0.000	Accepted

OAA -> ATA -> HMS	0.112	0.066	1.703	0.089	Accepted
HR -> ATA -> HMS	0.012	0.064	0.188	0.851	Rejected
SAV -> ATA -> HMS	0.104	0.051	2.032	0.042	Accepted
CE -> ATA -> HMS	0.245	0.073	3.358	0.001	Accepted

The above table has shown that ATA (ß = 0.251, $p < 0.05$) significantly and positively mediates the effect of CP on HMS. ATA (ß = 0.317, $p < 0.05$) significantly and positively mediates the effect of RA on HMS. ATA (ß = 0.077, $p > 0.05$) insignificantly and positively mediates the effect of TTF on HMS. ATA (ß = 0.012, $p > 0.05$) insignificantly and positively mediates the effect of SPC on HMS. The above table has also shown that ATA (ß = 0.193, $p < 0.05$) significantly and positively mediates the effect of TMS on HMS. ATA (ß = 0.112, $p < 0.05$) significantly and positively mediates the effect of OAA on HMS. ATA (ß = 0.012, $p > 0.05$) insignificantly and positively mediates the effect of HR on HMS. The above table has shown that ATA (ß = 0.104, $p < 0.05$) significantly and positively mediates the effect of SAV on HMS. ATA (ß = 0.245, $p < 0.05$) significantly and positively mediates the effect of CE on HMS.

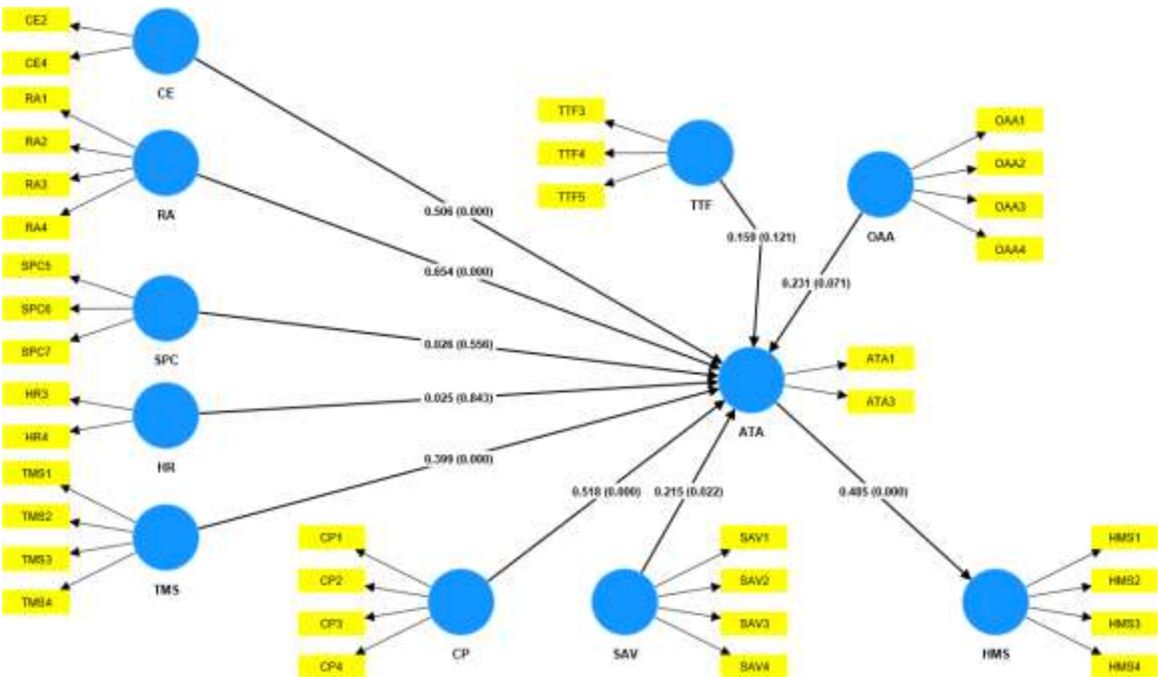

Figure 4.2: PLS Bootstrapping

5. Discussions

The results have shown that ATA has a positively significant effect on HMS. This result is consistent with Pillai and Sivathanu (2020). By automating tedious processes like resume screening and scheduling, AI in talent acquisition increases productivity and frees HR managers to concentrate on making strategic decisions. Insights derived from data are also offered for improved applicant selection. AI also lessens prejudice throughout the recruiting process, encouraging inclusiveness and diversity. These advantages result in better hiring practices, better results, and ultimately, satisfied HR and talent acquisition managers (Jose, 2019).

The study outcomes have revealed that CE has a positively significant effect on ATA. This result is supported by Pillai and Sivathanu (2020). AI-enabled talent acquisition lowers expenses through resource allocation optimization, simplification, and reduced manual labor. Due to AI's improved ability to target applicants, recruitment advertising costs are reduced. Additionally, HR professionals may focus on higher-value work by freeing up crucial time by automating administrative processes. AI's cost-effectiveness in talent acquisition improves ROI and resource utilization, which makes it a desirable choice for businesses looking for effective and affordable hiring solutions (Malik et al., 2022).

In addition, CP has a positively significant effect on ATA. This result is consistent with Subashini and Velmurugan (2023). Organizations are under pressure from the competition to find creative ways to acquire talent effectively. By allowing speedier, data-driven decision-making and hastening applicant placements, AI use in recruiting gives businesses a competitive edge. In an increasingly competitive marketplace, it improves the capacity to recognize and draw in outstanding talent. Furthermore, AI-powered technologies can quickly sort through enormous application pools to ensure qualified applicants are not passed over. Ultimately, using AI in talent acquisition boosts a company's competitiveness by keeping it ahead of the competition for the finest talent (Pillai & Sivathanu, 2020).

The study outcomes have revealed that HR has a positively insignificant effect on ATA. This result is supported by Gupta et al. (2022). The reason for this is that organizational priorities and technology readiness do not always coincide. HR professionals may not be ready to use AI, even if they are, for many reasons, such as financial limitations or managerial choices. Furthermore, other stakeholders' opposition or ignorance of AI technology might impede its application, decreasing the influence of HR readiness in the decision-making process. Therefore, even with HR readiness, organizational dynamics could be more critical in determining if AI is used in talent acquisition (Bhagyalakshmi & Maria, 2021).

Also, OAA has a positive and significant effect on ATA. This result is consistent with Bhalerao et al. (2022). Adopting AI-enabled talent acquisition is strongly influenced by one's attitude toward AI adoption. An organization that embraces AI proactively shows that it is eager to invest in cutting-edge technology for hiring. This kind of thinking encourages creativity and flexibility, which increases the likelihood that HR and talent acquisition departments will investigate and use AI technologies. Furthermore, a strong orientation toward AI adoption indicates a dedication to maintaining efficiency and competitiveness in the hiring process, which supports the beneficial effects of this mentality on AI adoption in hiring (Budhwar et al., 2022).

The study outcomes have revealed that RA has a positive and significant effect on ATA. This result is supported by Siripipatthanakul et al. (2022). Organizations are more likely to adopt AI-driven solutions when they show a clear advantage over conventional techniques in accuracy, cost-effectiveness, and efficiency. The benefits of AI adoption are clear and robust, including decreased prejudice, faster procedures, and data-driven decision-making. This relative advantage reinforces the favorable impact of the deployment of AI in talent acquisition by improving recruiting outcomes and positioning the company as competitive and forward-thinking in attracting top talent (Arora et al., 2023).

Moreover, SAV has a positively significant effect on ATA. This result is consistent with Chugunova and Danilov (2023). The possible explanation is that a reputable provider provides essential implementation support, handles technical problems, and offers required training. By providing confidence, this support helps to allay any fears or obstacles to adoption that may arise for HR teams. A proactive provider also guarantees a seamless transition, optimizing the advantages of AI in hiring. As a result, solid vendor support creates an atmosphere of expertise and confidence conducive to the effective integration of AI-enabled talent acquisition solutions (Siripipatthanakul et al., 2022).

Furthermore, SPC has a positively insignificant effect on ATA. This result is supported by Okeyika et al. (2023). Robust security controls and compliance regulations may frequently alleviate issues. Therefore, the adoption of AI in talent acquisition may be favorably insignificantly impacted by security/privacy concerns. Data security is a top priority for reputable AI providers who provide encryption and safe methods. Organizations might also impose stringent rules and regulations regarding privacy. Perceived security and privacy issues lose some of their power during the decision-making process when appropriate precautions are in place, which means that their influence on adoption is negligible compared to other considerations (Saha et al., 2023).

TMS has a positive and significant effect on ATA. This result is consistent with Subashini and Velmurugan (2023). A strategic commitment to innovation is signaled when executives support the application of AI. Their support distributes resources, guarantees interdepartmental collaboration, and establishes a standard for the entire company. This assistance encourages a culture that is receptive to innovation and technology development, which inspires HR departments to use AI-powered talent acquisition strategies. The backing of upper management offers the required stimulus for successful integration, enhancing the favorable influence on the implementation of AI in recruiting endeavors (Pillai & Sivathanu, 2020).

The study outcomes have revealed that TTF has a positively insignificant effect on ATA. This result is supported by Gupta (2022). Adopting AI in talent acquisition may be positively impacted by task-technology fit. However, this effect may not always be statistically significant because the technology may not always be aligned with particular activities. The degree to which the technology is a good fit for the activities at hand may nevertheless be compromised by organizational goals, financial restraints, or managerial choices. The choice to employ AI in talent acquisition may also be influenced less by task-technology fit and more by user-friendliness, ease of integration, and overall organizational preparedness (Bhagyalakshmi & Maria, 2021).

The results also reveal that ATA significantly and positively mediates the effect of CP on HMS. This result is consistent with Pillai and Sivathanu (2020). The rationale is that recruiting must be done accurately and efficiently in a competitive setting. Processes are streamlined with AI, allowing for faster, data-driven decision-making—more effective hiring results from this, which raises HR satisfaction. AI also enhances applicant selection and lessens prejudice, improving recruiting outcomes. Therefore, using AI in talent acquisition is a potent mediator, enhancing the beneficial effects of competitive pressure on employee satisfaction (Guenole & Feinzig, 2018).

Additionally, ATA significantly and positively mediates the effect of RA on HMS. This result is supported by Votto et al. (2021). This is because enhanced recruiting outcomes are directly impacted by AI's evident advantage over conventional approaches in efficiency, accuracy, and cost-effectiveness. Consequently, HR satisfaction is raised. Better candidate placements are also a result of AI-facilitated data-driven decision-making and simplified procedures. As a result, using AI increases the benefits of relative advantage and strengthens its effect on the general contentment of HR/talent acquisition managers (Arora et al., 2023).

The study outcomes have revealed that ATA insignificantly and positively mediates the effect of TTF on HMS. This result is consistent with Faqihi and Miah (2023). The task-technology fit and HR/talent acquisition managers' satisfaction may be positively mediated by using AI-enabled talent acquisition but in a negligible way. Task-technology fit is crucial, but it might not be the main factor influencing satisfaction. Budgetary restrictions and organizational goals, for example, may have a more significant impact than this fit. However, when AI is used appropriately, it may improve productivity, cutting down on manual labor and freeing HR managers to concentrate on strategic choices. This increases HR managers' satisfaction, but not much (Ramesh & Das, 2022).

Also, ATA insignificantly and positively mediates the effect of SPC on HMS. This result is supported by Okeyika et al. (2023). The adoption of AI-enabled talent acquisition may play a little but constructive mediating function between HR/talent acquisition managers' satisfaction and security/privacy concerns. Even though security and privacy are important factors, these issues may frequently be sufficiently addressed by effective procedures and compliance requirements. AI technologies have the potential to improve data security when appropriately used. As a result, HR managers may feel more certain and confident, which may enhance their level of satisfaction—though not much more than other influencing variables (Pandita & Yadav, 2022).

Likewise, ATA significantly and positively mediates the effect of TMS on HMS. This result is consistent with Subashini and Velmurugan (2023). When senior leadership supports using AI, it shows a strategic dedication to innovation and provides the required organizational support and resources. Processes are streamlined using AI, allowing for more accurate and efficient hiring. Better results follow, which eventually raise HR managers' satisfaction levels. The implementation of AI has been shown to benefit HR/talent acquisition managers' overall satisfaction, which is further supported by the top management's strong support (Pillai & Sivathanu, 2020).

The study outcomes have revealed that ATA significantly and positively mediates the effect of OAA on HMS. This result is supported by Bhalerao et al. (2022). The reason is that proactively embracing AI demonstrates an organization's dedication to innovation. When AI is used effectively, it simplifies procedures and makes data-driven, quick decisions possible. This improves hiring results and raises HR managers' level of satisfaction. The benefit of HR/talent acquisition managers' overall satisfaction is further amplified by the congruence between AI implementation and a forward-thinking approach (George & Thomas, 2019).

Similarly, ATA insignificantly and positively mediates the effect of HR on HMS. This result is consistent with Pillai and Sivathanu (2020). HR readiness is crucial, but it might not be the only factor determining satisfaction. In determining satisfaction levels, other organizational elements and outside circumstances may be more critical. HR managers' satisfaction may be positively impacted by AI adoption if HR is ready for it, although not much more than other influencing variables. AI adoption may increase efficiency and effectiveness in talent acquisition operations (Bhagyalakshmi & Maria, 2021).

Also, ATA significantly and positively mediates the effect of SAV on HMS. This result is supported by Chugunova and Danilov (2023). Reputable vendors handle technical problems and provide essential training and critical help throughout deployment. This assistance reduces any worries and adoption obstacles by boosting the trust of HR staff. Furthermore, a proactive vendor guarantees a seamless transition, optimizing the advantages of artificial intelligence in hiring. Strong vendor support, then, creates a basis of expertise and confidence that is conducive to the effective integration of AI-enabled talent acquisition solutions (Siripipatthanakul et al., 2022).

Lastly, ATA significantly and positively mediates the effect of CE on HMS. This result is consistent with Budhwar et al. (2022). The rationale is that artificial intelligence (AI) optimizes resource allocation, reduces manual labor, and simplifies procedures, lowering hiring costs. HR managers may concentrate on making strategic decisions due to this efficiency. Furthermore, AI-powered technologies can quickly go through enormous application pools to ensure qualified applicants are not passed over. HR and talent acquisition managers report greater satisfaction as a direct result of cost savings and better recruiting outcomes (Li et al., 2021).

6. Conclusion and Recommendations

6.1. Conclusion

The study investigated the factors affecting HR/TA managers' satisfaction and the adoption of AI-enabled TA. The study also examined how task technology fit and orientation toward AI adoption influenced the adoption of AI-enabled TA, revealing that AI has a huge potential to increase efficiency and effectiveness in the talent acquisition process. The study has chosen HR and talent acquisition managers of manufacturing firms in Karachi as a sample population, while the survey approach is used to gather the data. The current study has utilized PLS-SEM for data analysis. The results have revealed that ATA has a positively significant effect on HMS. CE, CP, OAA, RA, SAV, and TMS have a positively significant effect on ATA. While HR, SPC, and TTF have a positively insignificant effect on ATA. SPC has a positively insignificant effect on ATA. TTF has a positively insignificant effect on ATA. Furthermore,

ATA significantly and positively mediates the effect of CP, RA, TMS, OAA, SAV, and CE on HMS. ATA insignificantly and positively mediates the effect of TTF, SPC, and HR on HMS.

This research, on its whole, sheds light on the revolutionary possibilities of incorporating AI into talent acquisition (TA) strategies. It is clear from extensively researching HR and TA managers' experiences in Karachi's industrial sector that artificial intelligence (AI) is a key component in altering traditional recruiting and hiring procedures. The findings highlight how urgently businesses must consider integrating AI into their TA procedures. Not only does this have great potential for improving operational efficiency, but it also speaks well for increasing talent acquisition competitiveness. This study makes a strong case for the HR industry to actively adopt new technology actively, eventually changing the course of talent acquisition strategies.

6.2. Theoretical implications

The current study has provided many theoretical implications. First, a conceptual model was developed to understand the adoption of AIT for TA while considering TTF (Gupta, 2022). D-TOE model was employed in this study to examine how well AIT suited TA functions by understanding the task technology fit. Also, this study included new variables like HRR and COS to understand better the usage of AI-enabled TA (Pillai & Sivathanu, 2020). Second, there is a paucity of studies on how emerging and disruptive technologies, like artificial intelligence, are used. However, this study extends the body of literature on technology adoption, which makes it a precious contribution to the current theoretical frameworks (Bhagyalakshmi & Maria, 2021).

Similarly, the proposed model provided crucial insights that help researchers, academicians, and practitioners understand and develop the study of how HR managers represent the organizational viewpoint when they use AI for TA. The study model empirically supports the TTF and substantially explains the adoption of AI-enabled TA for HR managers' satisfaction in manufacturing firms. (Faqihi & Miah, 2023).

6.3. Recommendations

The study has provided several recommendations. First, this study provided a valuable framework for understanding the adoption of AI for TA functions in the context of a developing economy. This study also showed that SNP impacts how AI-enabled TA is adopted. This indicates that SNP is a problem for TA managers, and as a result, AIT developers and designers must ensure the same while creating AIT-based TA solutions. Marketers should provide training on data security and privacy. Prior to deployment, AIT vendors should let HR managers know about the security aspects that should be integrated into AI for TA. Second, HR managers are eager to use the technology due to the cost-effectiveness and REA of AI for TA. These factors have shown HR professionals how AIT effectively improves TA function by reducing TA costs and time. It was found that top management support (TMS) and HRR affected the adoption of AI-enabled TA. They understand the significance and have budgeted allowances for investing in AI technology. This indicates to AIT marketers that there is a significant need for AIT for TA among top management and HR managers in firms.

Lastly, it was found that vendor support also impacts adoption, implying that AIT providers should provide technological support before, during, and after implementation to guarantee that AIT for TA is successfully adopted. As AI is a new technology for HR managers, vendors must provide assistance and prompt inquiry responses during the AIT for TA implementation. HR managers must also consider the AI technology's compatibility and suitability for TA functions according to the organization's requirements when acquiring AIT for TA.

6.4. Limitations and future research

First, this study exclusively surveyed manufacturing firms in Karachi and obtained data from HR and talent acquisition managers. Future studies might be focused on various industries to generalize the findings and should collect data from different populations. Second, this study focused on the impact of AI-enabled TA adoption on HR/TA managers' satisfaction. Future research may examine how AIT affects an organization's performance, employer branding, and the actual use of AI for TA. As this study was quantitative, the statistical analysis of the questionnaire further limited its findings. Future research should adopt a qualitative methodology to produce robust data validation findings. The study model only had a few variables, which may be improved by including more significant variables. The comprehensive research model may include more theories and constructs to enhance its capacity for explanation in the future. Also, the study used PLS-SEM for data analysis. Future studies should use different statistical tools for data analysis.

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