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Adoption of AI for Talent Acquisition in the IT industry of Pakistan

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Abstract

The adaptation and use of artificial intelligence has exponentially increased overtime and that is not limited to any single industry. Companies have incorporated AI to streamline and enhance their Talent Acquisition processes. The objective of the research was to examine the effect of perceived value on adoption of AI in talent Acquisition and to identify the function of moderating variable of HR Readiness in relation with intention to adopt AI. A structured 5-point Likert scale questionnaire was circulated amongst employees of IT department and the HR department in IT companies of Pakistan. A total of 70 responses were collected. The research paper used the Value-Based Adoption Model (VAM) as it concentrates on the intention of recent technology and how it talks about the concern of prospective adapters. To develop and evaluate the data, Partial least squares structural equation modeling (PLS-SEM) was used on the SMART PLS software. In this research, purposive sampling technique was used as the study revolved around gathering data from the selected individuals based on the predetermined criteria. The findings of the study showed that perceived value has a significant positive relationship with Adoption of AI, and HR Readiness as a moderating variable also has a positive significant relation with Adoption of AI. It is determined that AI technology has the potential to completely change the systems and not just in the IT industry but in several others as well. Companies must make sure that they monitor the AI tools being used in the TA process to ensure unbiased decisions in the recruitment process.

Keywords Artificial Intelligence, HR Readiness, Perceived Value, AI Adoption.

Introduction

Background of Study

In modern terminology, artificial intelligence is the ability to reason, communicate and operate similar to that as of a human. The word "Artificial Intelligence" or AI is also being used as synonym for "machine learning or "deep learning" (Du-Harpur et al., 2020). The main features of this technology are problem-solving, forecasting, responding to situations and creating its own guidelines. However, recently AI has developed it selves to achieve a goal independently (Dal Mas et al., 2019).

Like many other departments, AI has developed itself as the building block in the HR department as well (Alam et al.,2020) This usage is not just limited to operational tasks but in recruiting high- quality talent as well. As compared to the past, Talent acquisition is not limited to filling vacant positions now. It is a strategic, long-term approach to find the appropriate person for the right position. From finding specialists to developing future leaders, all comes under the umbrella of Talent Acquisition. The competitive job market and high demand for skilled workers has led the TA process to become more efficient, requiring constant attention (Vedapradha et al., 2023). As the trend of digitalization has increased, researchers have delved deep into the adoption of AI technology. HR managers and TA specialists are turning towards AI tools as a helping hand for efficient recruitment processes. Artificial Intelligence streamlines the Talent Acquisition process by automating some time-consuming tasks like recruitment and selection (Sattu et al., 2024).

Due to global technological breakthroughs there has been a significant technological surge this year. A KPMG report that estimates investments in robotic process automation (RPA), artificial intelligence (AI), and machine learning (ML) would surpass $232 billion by 2025 supports this trend (Schweikl and Obermaier, 2020). The importance of AI is underscored by the substantial investments of leading global corporations like Google, Facebook, Microsoft, and others. This emphasis is further reflected by the extensive research conducted in developed nations on AI's application in talent recruitment across various industries. A significant body of empirical research now exists on organizational-level AI adoption (Alam et al., 2020). However, as compared to many countries in the west, the investments on AI is significantly low in Pakistan. The Pakistani IT industry has a limited use of AI tools which has impacted its adoption in the HR department as well.

While many multinational companies have embraced AI expertise and technology to streamline hiring processes, there are still holdouts (Sharma and Kuknor, 2021). This highlights the need for deep research into whether HR and IT managers are comfortable adopting AI for recruitment purposes for both technical and non-technical. Existing literature explores AI adoption at both organizational and employee levels (Van Esch et al., 2019).

The role of artificial intelligence (AI) in human resource management is expanding rapidly. AI can now be implemented in three distinct phases: Assisted Intelligence, Augmented Intelligence, and Autonomous Intelligence. Assisted Intelligence utilizes AI tools to streamline repetitive tasks, with chatbots and similar technologies offering support to employees in various aspects of their work. Augmented Intelligence represents a collaborative approach, where AI and human intelligence work together to make informed decisions. Lastly, Autonomous Intelligence signifies a transformative shift in the workplace, with AI systems operating independently and reaching conclusions based on gathered and analyzed data (Albert ET, 2019)

In context to Talent Acquisition, AI automates tedious, repetitive tasks like screening and initial candidate evaluations. This allows Talent Acquisition specialists to swiftly pinpoint the most qualified applicants and speed up the recruitment process (Hmoud and Laszlo, 2019). AI algorithms analyze candidate data to match them with job requirements based on skills and experience. This leads to a more accurate and efficient identification of top talent for specific roles. Furthermore, AI can decrease recruitment costs by automating tasks and minimizing human involvement. Therefore, the utilization of AI in talent acquisition leads to enhanced recruitment results, increased efficiency, and cost reduction (Johnson et al.,2020). However, the rate of adoption of AI for recruitment purposes have been slow with context to Pakistan. There can be several reasons like problems arising from technological advancements, trust issues, cost effectiveness, benefits and sacrifices. There have been many researches in the benefits and usage of AI in the recent years but each of them has its own limitations.

Traditional technology adoption models like TAM (Technology Acceptance Model) and UTAUT (Unified Theory of Acceptance and Use of Technology) focus on perceived benefits and sacrifices in relation to the total supposed value. However, these models primarily address individual-level technology adoption challenges and overlook adoption intentions at the organizational level.

Additionally, previous research hasn't considered HR readiness as a moderating or mediating factor in AI adoption. Furthermore, the impact of factors mistrust and security concerns on perceived sacrifices haven't been explored in depth previously as well.

This study aims to address these adoption challenges by proposing a model built on existing concepts that specifically examines the use of AI in talent acquisition. We examine the impact of perceived sacrifices and advantages on the overall value as a result of AI adoption, as outlined by the value-based adoption model. HR readiness, with its potential benefits, has been extensively researched as a factor influencing adoption. Our research aims to contribute to the body of knowledge surrounding technology adoption specifically in the context of talent acquisition.

It has been observed that previous studies have limiting literature upon the adoption of AI within the IT industry of Pakistan. The growing fascination with AI in HR, particularly talent acquisition, and the limited research on navigating its implementation, motivate this research into AI's role in the field.

Problem Statement

There are many international firms that leverage AI technology to enhance their recruitment process, however in Pakistan there is limited research. There is also a lack of research to understand HR managers' perspectives on its adoption. Moreover, previously the models that were used were technology adoption model (TAM) and unified theory of acceptance and use of technology (UTAUT). These models don't fully address the benefits and challenges of AI in this context. These models also overlook factors like perceived benefits and sacrifices of AI, as well as HR Readiness. Researches on technological advancement has considered security and lack of trust as a factor, but existing research hasn't factored in an organization's HR department's readiness for adopting AI in Pakistan. The potential negative impact of security concerns and a lack of trust in AI hasn't been adequately addressed in previous research. These factors can significantly influence HR managers' decisions regarding AI adoption.

GAP Analysis

Previous research has focused on HR professionals' perspectives on AI adoption. This study considers IT professionals and explores the perspectives of both groups. The incorporation of IT professionals alongside HR professionals in this research stems from a desire to gain a more comprehensive understanding of AI adoption in talent acquisition. IT professionals possess a deep understanding of AI technology, its capabilities, limitations, and potential integration with existing HR systems. Their insights are invaluable in evaluating the feasibility and effectiveness of implementing AI for talent acquisition tasks. Additionally, after implementation, ongoing training and support for both HR and talent pool candidates using the AI system are crucial. IT professionals can play a key role in developing training programs and providing technical support for users unfamiliar with the AI technology.

In contrast to prior studies, this research employed the VAM model to analyze how HR professionals weigh the pros and cons of AI in talent acquisition to determine its overall value. The VAM model explains why people choose to adopt new technologies. It suggests that people weigh the pros and cons before making a decision. The pros, are the benefits they expect to receive from using the technology, such as usefulness. The cons, are the sacrifices they have to make, like time or effort. This VAM model builds on both the TAM (Technology Acceptance Model) and Zeithaml's concept of perceived value to provide thorough grasp of technology adoption in our rapidly evolving technological world (Zheithaml, 1998)

Research Objectives

This research delves into the adoption of AI for talent acquisition within the Pakistani IT industry. By incorporating the perspectives of various stakeholders, the study aims to identify potential challenges and opportunities associated with this technological shift. The focus lies on understanding how the implementation of AI might impact traditional recruitment practices and whether such practices might prioritize efficiency over human judgment or ethical considerations in the recruitment process. The research proposes further investigation through the formulation of targeted research questions to gain a more comprehensive understanding of AI adoption for talent acquisition within the specific context of the Pakistani IT sector. Based on this, following research questions were formulated:

1. Investigate the impact of perceived value on the adoption of AI in talent acquisition.
2. Examine the influence of security, privacy concerns, usefulness, innovation resistance, cost-effectiveness, and trust on perceived value.
3. Determine the relationship between HR readiness and AI adoption.

Research Questions

1. What is the impact of perceived value on Adoption of AI?
2. What is the impact of security and privacy concerns, usefulness, innovation resistance, cost effectiveness, trust on perceived value?
3. What is relationship between HR Readiness as a moderator with respect to Adoption of AI?

Significance of Study

The purpose of this research is to provide a benefit in understanding the importance of raising awareness regarding AI adoption. By highlighting the advantages of AI, this research can encourage Pakistani IT businesses, especially those new to the technology, to integrate AI into their talent acquisition processes. Additionally, this research can be beneficial to HR professionals and IT professionals within the industry by providing them with actionable steps and best practices to make AI adoption in talent acquisition more efficient, secure, and trustworthy.

Literature Review

Researchers have explored various models to understand how people adopt information systems. This study proposes a new model, the Value-Based Adoption Model (VAM), which is centered on the advantages of the technology. Existing models have limitations, such as focusing on individual users or neglecting the value proposition. Some famous models include Theory of Reasoned Action (TRA) (Ajzen and Fishbein, 1980), the diffusion of innovation (DOI) theory (Rogers, 2005), Technology Acceptance Model (TAM) (Davis and Davis, 1989), technology- organization-environment (TOE) model, Task Technology Fit (TTF) (Goodhue and Thompson, 1995) and Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al., 2003)

The TAM Model (Davis and Davis, 1989) is a widely used framework for understanding how people adopt new technologies. It proposes that perceived usefulness and perceived ease of use are the key drivers of adoption. In simpler terms, if people think that the technology is useful and simple to use, they will embrace it. Although it is a popular model and many researches use it, there are some limitations. Firstly, it focuses primarily on individual user acceptance and usage behavior. This means it doesn't consider the broader social, organizational, or cultural factors that might influence adoption decisions. For instance, a company culture resistant to change or a lack of organizational support for a new technology could hinder its adoption, even if individuals find it seemingly useful and easy to use.

While the Diffusion of Innovations (DOI) and Technology Acceptance Model (TAM) models have significantly contributed to our understanding of technology adoption, both frameworks have limitations. TAM, by Davis (1989), focuses heavily on perceived usefulness and ease of use at the individual level. This oversees the impact of organizational, social and cultural factors that might impede adoption, even if individuals find the technology appealing.

The value-based adoption model (VAM) highlights the new technology’s value and how it aligns with the requirements of possible users. It suggests that perceived benefits, such as higher productivity, lower expenses, better outcomes, and an improved user experience, are what motivate adoption. The VAM model pinpoints and focuses on the major factors that influence adoption. The model underscores the importance of understanding the value proposition of new technology and how it fulfills the needs of potential adopters. The model emphasizes how crucial it is to comprehend the worth presentation of groundbreaking technology and how it satisfies prospective users' needs. Through an emphasis on its advantages and the resolution of significant adoption barriers, the VAM model can help enterprises successfully integrate new innovations and technology. Similarly, Diffisuion of Innovation (Rogers and Cartano, 1962), categorizes adopters and emphasizes factors like relative advantage and complexity, but it primarily focuses on individual characteristics like age and education. This model neglects the crucial role of social networks, opinion leaders, and broader cultural norms that can significantly influence the overall diffusion of a technology within a community. Therefore, while both models offer valuable insights, a more comprehensive understanding of technology adoption requires acknowledging the interplay between individual perceptions, social influences, and the surrounding cultural context.

The Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al., 2003) expands on TAM and further models. It identifies four key drivers of technology adaptation which are termed as performance expectancy, perceived ease of use and facilitating conditions availability of resources and support. Additionally, UTAUT acknowledges that demographics like gender, age, and technological experience can influence these factors. However, the model emphasizes on individual-based technology adoption and use. It doesn't delve into the broader organizational or societal factors that can significantly impact the decision to adopt and utilize a technology. Furthermore, UTAUT has been criticized for its limitations in predicting technology adoption with perfect accuracy. While it offers a valuable framework, it's important to recognize these limitations for a more complete understanding of the complex factors influencing technology adoption.

The technology-organization-environment (TOE) model (Dipietro et al., 1990) is extensively utilized in the examination of the various elements that exert influence on the adoption of technology at the organizational level. It postulates that the factors that affect the adoption of technology have repercussions both within and outside the realms of enterprises. It is imperative for organizations embracing a comprehensive technology organisation environment model to ensure that such adoption is not only efficient but also upholds principles of ethics and sustainability in the long run. Moreover, this model places its emphasis primarily on the examination of macro-level aspects including technology, organization, and environmental attributes. Conversely, it tends to overlook the significance of individual-level elements such as user attitudes, perceptions, and behaviors, all of which can exert a considerable influence on the adoption and execution of technology.

The concept of Task Technology Fit (TTF) (Goodhue and Thompson, 1995), presents a framework that delves into the intricacies of how individuals leverage technology to achieve specific objectives by taking into account the various features and capabilities it offers. A common hindrance often highlighted in literature regarding technology adoption pertains to the limitations of technology in meeting complex task requirements. While the Technology-Organization- Environment (TOE) and Task Technology Fit (TTF) models have been instrumental in exploring the dynamics of adoption within an organizational context, an area that remains inadequately addressed is the decision-making process undertaken by companies when procuring a new system. This gap is particularly evident in the failure of the TOE model to effectively elucidate the cost- benefit analysis of technology within corporate settings. By expanding the existing paradigm to integrate elements from the TOE model, the Value-Based Adoption Model emerges as a comprehensive framework that seeks to rectify these deficiencies and offer a more holistic perspective on technology adoption processes.

The Value-Based Adoption Model (VAM) takes a different approach to understanding technology adoption. Instead of focusing on individual user perceptions or adopter categories, VAM emphasizes the value proposition of the new technology. In simpler terms, it asks: "What benefits does this technology offer, and how does it address the needs of potential users?" (Sattu, 2024)

VAM suggests that the perceived value of a technology, encompassing factors like increased efficiency, cost reduction, better outcomes, and improved user experience, is the key driver of adoption. By identifying the key components that influence people's decision to adopt a new technology, VAM helps organizations understand what matters most to potential users.

This model highlights the importance of clearly communicating the value proposition of a new technology. When organizations demonstrate how a new technology can address user needs and overcome adoption barriers, it increases the chances of successful adoption and integration within the organization.

Therefore, this research utilizes an extended VAM framework to build its model and formulate its hypotheses. This extended framework likely incorporates additional factors beyond the core value proposition to provide a more comprehensive understanding of technology adoption.

This model was originally created to better understand the factors that impact Mobile Internet adoption (Kim et al., 2007). However, from a value maximization perspective, the Value Adoption Model (VAM) offers a clearer understanding of the elements that influence value perception and explains how it can lead to adoption (Chang and Nam, 2021) In this study, perceived benefits include cost-effectiveness, relative advantages, and utility.

According to R. Vedapradha et al., (2023) Talent Acquisition has the positive and significant correlation along with its actual usage. Candidate experience is the top influencing variable from the first factor, Competency and ease of use is the also have high correlation in the second factor. Talent Management is the highest analyst as a variable of using the technology and its adoption is the most influencing predictor in the effective implementation of the technology among the IT organization.

The study collected by Bano et al., (2022) was on AI For Talent Acquisition in the manufacturing industry in Pakistan. The independent variables discussed in this research are HR readiness, cost effectives, relative advantage, security and privacy concern, Top management support, competitive pressure and the dependent variable was Adoption of AI for Talent Acquisition. However, this was an independent variable for HR/TA manager satisfaction. The findings revealed that the adoption of AI-led recruitment has a positive and significant impact on HR/TA manager's contentment. Moreover, competitive pressure, cost-effectiveness, relative advantage, top management support and support from AI vendors have a positive impact on the adoption of AI- led recruitment. In contrast, an attitude towards AI adoption has a minor positive influence on the adoption of AI-enabled TA. However, privacy and security issues, HR preparedness, and task- technology fit have little impact on AI-enabled talent acquisition. Furthermore, implementing AI- enabled recruitment improves the relationship between all independent components and HR/TA manager satisfaction, with the exception of HR readiness, security and privacy concerns and task- technology fit.

According to Rind et al., (2017) perceived risk, cost and behavioural intention have a negative impact on adoption M-commerce among Pakistani consumers. This showed that the consumers are hesitant to adopt any technology, be it AI or e-commerce. The findings also show that, PEOU, and perceived utility are major important factors influencing the behavioural intention to adopt M-commerce.

Bancoro (2024) researched upon Exploring the Influence of Perceived Usefulness and Perceived Ease of Use on Technology Engagement of Business Administration Instructors and the findings revealed that Perceived usefulness plays a crucial role in technology adoption across various domains and has a significant impact on technology adoption. Similarly, in a study by Anaam et al., (2023) usefulness is highlighted as a critical factor influencing technology adaptation, particularly when supported by compatibility and self-efficacy among users.

As the adoption of AI is not limited to the IT industry, many sectors in Pakistan are using it for their own ease. Akram et al., (2024) researched upon transformation in healthcare with artificial intelligence in Pakistan. The findings showed an increased level of knowledge among participants regarding AI applications in healthcare, with most of them expressing positive attitudes toward its incorporation into clinical practice. It was concluded that there is a significant relation for the integration of artificial intelligence. The use of artificial intelligence is blooming in the business sector around the globe, hence it is necessary to understand the factors influencing the acceptance and trust of AI tools in recruitment for its successful implementation. Akram et al., (2024) in their research found out that Data privacy and security concerns play a significant role in the adoption of AI in healthcare in Pakistan. These concerns act as barriers to the widespread implementation of AI technologies. Protecting patient privacy and ensuring secure storage and transmission of data are essential to maintain patient trust and comply with regulatory requirements in the healthcare sector.

Hosseini at al., (2016) researched upon the factors that affect resistance when it comes to adapting mobile technology. The findings revealed that Relative advantage has a significant negative effect on consumers' resistance to mobile phones. Respondents who perceive mobile phones as relatively more advantageous as normal phones express less resistance. The research also focused upon Perceived risk, which is a crucial factor in consumer decision-making regarding the adoption of new products. It is one of the consumer-dependent factors that influence the adoption of

innovations. The level of risk associated with a new product can impact consumers' resistance to adopting it. Understanding and addressing perceived risk is essential for increasing the success of innovation initiatives. Their findings suggest that highlighting the relative advantage of AI compared to existing methods can significantly reduce innovation resistance. When individuals perceive AI as offering clear benefits over traditional approaches, they're less likely to resist its adoption. Similarly, addressing perceived risks associated with AI, such as job displacement or privacy concerns, is crucial for overcoming resistance.

Hmoud and László (2021) researched to investigate HR leaders' trust in AI application in recruitment and the role of technology trust as a forecaster of HR leaders' attitude. The study results showed that HR leaders have a positive effect toward the adoption of AI applications in the recruitment function. Furthermore, HR leaders saw it favourably, which affected their attitude. Additionally, it is established that HR leaders have a high level of trust in AI-based TA solutions, and their perceptions of trustworthiness, credibility, and technical competence are strong determinants of this trust.

AI also has a major role in modernizing many industry that includes banking sector as well. To better understand the challenges and significance of AI adoption in the banking sector in Malaysia Rahman et al., (2023) conducted a comprehensive study on identifying factors that influence consumers' intention to adopt AI in banking services. . The findings showed that AI is an essential tool for risk prevention and fraud detection. The absence of regulatory requirements, absence of relevant skills, data privacy and security, and IT infrastructure are significant challenges of AI adoption. The quantitative findings indicate that perceived usefulness, attitude towards AI, perceived trust, perceived risk, and subjective norms have significant impact on the intention to adopt AI in banking services while perceived ease of use and awareness do not. The findings also demonstrate that attitude towards AI strongly influences the association between perceived usefulness and intention to employ AI in financial services.

Security and safety are crucial aspects when considering AI systems (Balasubramaniam et al., 2023). In this previous research, the analysis of ethical guidelines from multiple companies revealed the importance of transparency, which is closely related to security and safety in AI systems. The importance of security and safety in AI systems is underscored by the near-universal emphasis on transparency within organizations. Essentially, the research identifies good practices for defining explainability, which ultimately translates to improved security and safety measures within AI system.

Unlike most of the researches on technology adoption, (Chatterjee et al., 2021) research findings showed that factors such as organizational readiness, organizational compatibility, and partner support do not directly impact the perceived ease of use of AI technologies in the context of digital manufacturing and production organizations. This challenges the traditional understanding of technology adoption, suggesting that even if an organization isn't fully prepared or lacks a perfectly compatible environment, the perceived ease of use of AI itself might be a strong driver for adoption. This research, focusing on AI adoption for talent acquisition in the Pakistani IT sector, contributes to this discussion by examining whether similar dynamics hold true in this context.

Our research delves into the adoption of AI for talent acquisition within the Pakistani IT industry. While the specific context of our investigation may differ, existing studies offer valuable insights into the factors influencing AI adoption in this domain. In another research conducted by Bano et al., (2019) HR readiness plays a significant role in the adoption of AI-enabled talent acquisition in the manufacturing sector of Pakistan. The study indicates that HR readiness is crucial for adopting AI-enabled TA. Relative advantage, top management support, competitive pressure, and support from AI vendors have a positive effect on the adoption of AI-enabled talent acquisition. Though their study focused on the manufacturing sector, the concept of HR readiness likely holds true across different industries, including the IT sector that our research is investigating. Furthermore, Bano et al.'s (2019) findings on "relative advantage" resonate across sectors. Their research suggests that organizations are more likely to embrace AI-enabled TA when they perceive a clear advantage over traditional recruitment methods. This translates to the IT industry as well. HR professionals in our research area, the IT sector, are likely to be more receptive to AI adoption if they see it as a tool that can streamline their recruitment efforts, attract top talent, or identify qualified candidates more efficiently. By understanding these broader trends and tailoring them to the specific context of the IT industry, our research can build upon existing knowledge and provide valuable insights for HR professionals seeking to leverage AI for more effective talent acquisition.

The landscape of education is also growing with the advancement of AI and researches have been carried on it as well. Vedapradha et al., (2024) have undertook a study to evaluate the feasibility and impact of AI applications in TA within higher educational institutions (HEIs) in India's metropolitan cities. Findings revealed that productivity, PEOU adaptability, candidate experience with the adoption of AI had the most significant and positive impact on the application of AI in TA.

Conceptual Model and Hypothesis Development

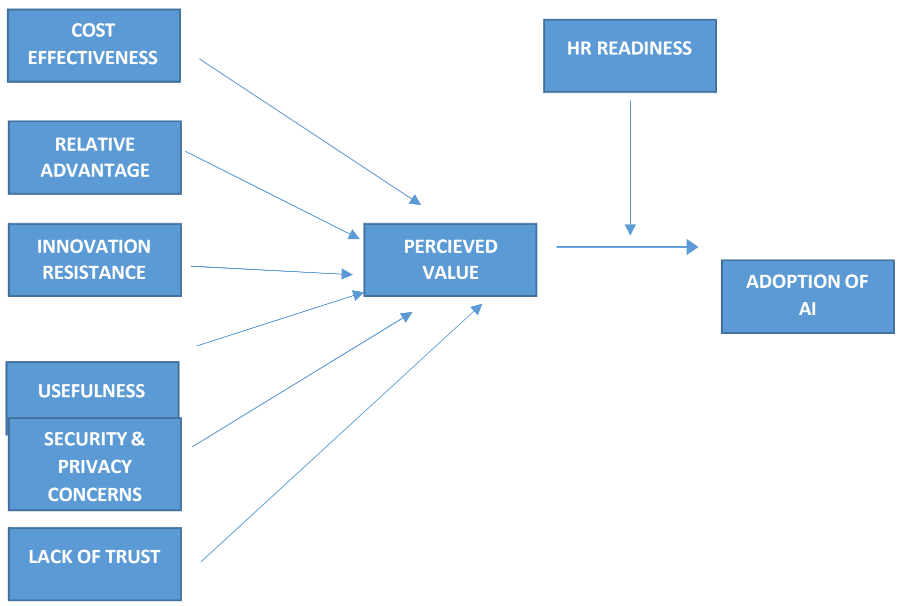


Figure 1: Conceptual Framework

Hypothesis Development

Relationship between Relative Advantage (RA) and Perceived Value (PV)

Rogers and William (1983) in their research describe relative advantage refers to the perceived superiority of an invention compared to the idea or product it replaces. Puklavec et al., (2018) also researched upon relative advantage and concluded that it is an important predecessor of information systems, HRIS, business analytics and intelligence adoption. Likewise, Lee and Lee (2004) said that the chances of adopting technology increases if it shows a competitive advantage over the current technology that is being used in a company. Mndzebele (2013) also said that argue that technology is most likely to be adopted when organisations perceive that it will help with the sharing of business information within an establishment. Based on the above, the following hypothesis can be put forward:

H1: Relative Advantage positively influences Perceived Value

1. Relationship between Innovation Resistance (IR) and Perceived Value (PV)

Innovation resistance refers to the obstacles that prevent technology adoption in a specific context. In talent acquisition, factors contributing to resistance in adopting AI include lack of awareness, fear of job loss, privacy and ethical concerns, as well as cost and complexity (Leesakul et al., 2022). A downside of using AI is that it prioritizes data points over candidate's full potential which might not capture a candidate's capabilities. AI can inherit and amplify biases from training data. This can lead to unfair screening and a lack of diversity in the talent pool. Based on the above, the following hypothesis can be put forward:

H2: Innovation Resistance negatively influences Perceived Value

2. Relationship between Usefulness (UF) and Perceived Value (PV)

Usefulness can be defined as a person's confidence that using a specific system, software or a service would benefit them in several ways (Rind, 2017). Recruiting high quality candidates become crucial for TA specialists due to multiple reasons existing within the organization (Landers and Schmidt, 2016). Hence it can be said that AI has the power to assist in drawing and hiring top talent efficiently by using advanced methods. Based on the above, the following hypothesis can be put forward:

H3: Usefulness positively influences Perceived Value

3. Relationship between Security and Privacy Concerns (SPC) and Perceived Value (PV)

Security and Privacy Concerns means an individual's perception regarding the insecurity of the data shared with different kinds of information system (Zhu and Xu, 2006). People have concerns regarding sharing their private data with information systems and technologies. There have been many researches in support of it. Low et al., 2011 says that technology adoption needs to improve as it must ensure the consumers that their data is safe. Yadegaridehkordi et al. (2020) study says that there is a negative impact on SPC on technology adoption. The technology used to recruit talent using AI has a lot of sensitive information like phone numbers, addresses and resumes. To ensure the safety of such personal information, the safety measure for AI adoption must be take accordingly. Based on the above, the following hypothesis can be put forward:

H4: Security and Privacy Concern negatively influences Perceived Value for AI adoption.

4. Relationship between Lack of Trust (LT) and Perceived Value (PV)

Candidates, employers and HR professionals do not normally trust AI for recruitment purposes due to many reasons such as, biasness, transparency and job security. People also fear that AI can replace human jobs. The jobs may include technical and HR related both. In some sectors AI also rises up the issue of security, legality, ethics and privacy of candidates. Balasubramaniam et al., (2023) in his research said that AI can be used in a moral and ethical way to avoid any negative candidate experience. Yet, the lack of trust has been an ever common concern for employees. Based on the above, the following hypothesis can be put forward:

H5: Lack of Trust negatively influences Perceived Value for AI adoption.

5. Relationship between Cost Effectiveness (CE) and Perceived Value (PV)

Cost Effectiveness can be defined as the benefits of adoption new technology exceed the costs of such technology (Premkumar and Roberts, 1999). Companies assess the costs compared to the benefits before choosing to adopt IT innovation. When consumers perceive a product or service as highly cost-effective, they may associate lower costs with reduced quality or benefits. This perception can lead to a diminished sense of value, as consumers might believe that the product's affordability compromises its overall utility. Consequently, even though the product is economically advantageous, the perceived value in the eyes of the consumer may be adversely affected. Based on the above, the following hypothesis can be put forward:

H6: Cost Effectiveness influences Perceived Value for AI adoption.

6. Perceived Value (PV)

Zeithaml (1988) defined perceived value as consumer's overall evaluation of a product's utility based on their perceptions of the benefits received versus the costs incurred. This made a very popular definition for the terminology and became a reference of many researchers. Hallowell (1996). Hallowell (1996) defined perceived value as equal to quality compared with the price. In the light of Adoption of AI for talent acquisition, HR managers, recruiters and candidates analyze that what the certain AI tools have to offer them. They need to be sure that whatever technology is being used is worth their time, money and price. Based on the above, the following hypothesis can be put forward:

H7: Perceived Value positively influences Perceived Value for AI adoption.

Mediation Analysis

HR readiness is the moderator of our research. It is defined as the required skills and resources to adapt AI technology (Sharma and Kuknor, 2021). There are a few researches that said HR readiness impacts adoptions while others has no impact on technology adoption (Ifinedo, 2011). As HR is using AI in talent acquisition, proactive budgeting has become a necessity. While traditional recruitment methods still remain in organizations, HR leaders are actively exploring new technologies. Based on the following analysis, following hypothesis can be made:

H8: HR Readiness positively influences Perceived Value for AI adoption.

Research Methodology

Research Paradigm

This research aims to understand the factors that influence the adoption of AI in IT industry of Pakistan. It also aims to understand the impact of perceived value on adoption of AI while HR readiness remains a moderating variable. Many researchers have worked upon the how professionals perceive the adoption AI in organizations, but the literature in Pakistan remains limited. Researchers from across the world have used different models to understand the technology adoption. However, all of them has inherent flaws which didn't fit fully into this research. Although the Technology Adoption Model (TAM) (Davus and Davis, 1989) is a popular model it had a limitation that it only focuses on individual level of technology and not the organization as a whole. Similarly, the Technology Organization Environment (TOE) (Dipietro et al., 1990) focuses on macro level factors such as organization, environment and technological characteristics. Hence, the present study adopted the Value-Based Model along with some paradigm from the TOE model in the Pakistani context.

Research Design

There are three types of approaches Quantitative, Qualitative, and Pragmatic approach (mixed methods). This study uses 'Quantitative research design and causal research. Quantitative research is a type of research that stresses on the quantification of data collection and its analysis. Meanwhile, causal research is also known as explanatory research that helps to analyze the cause- and-effect relationship between variables. As for the data collection method, a structured questionnaire was created on Google Docs that was circulated among IT companies in different cities of Pakistan.

Research Instrument

The study used a structured questionnaire and the data was collected from a total of 70 IT professionals and HR professions of the IT companies in Pakistan. The measurement scale was made using the VAM model and some paradigm of the TOE model. The constructs were adopted from previous researches to ensure validity. The detailed description of which is given in the table.

A 5-point likert scale was incorporated in the study where 1 being Strong Disagree and 5 Being Strongly Agree.

Normality Testing

Normality testing is an important part of a research that shows weather or not the data is available, ready for testing and well modeled by normal distribution. The statistical tests include regression analysis and many others. It is important to ensure normality as it tells us about the validity and the reliability of the results.

In this study, skewness and kurtosis was analyzed by examining the data collected by pilot testing. Skewness measures the asymmetry of the data distribution, while kurtosis measures the peakness or flatness of the distribution compared to a normal distribution. The results indicated that all values of kurtosis and skewness were above +3/-3 as shown in Table 1. Meanwhile the values of some variables who did not fall in this range were deleted.

Measure Utilized

Construct	Code	No. of Items	Author
	AAI1		(Awa et al., 2016)
	AAI2		
Adoption of AI	AAI3	4	
	AAI14		
	CE1		
Cost Effectiveness	CE2	3	(Puklavec et al., 2018; Chong and Chan, 2012)
	CE2		
	HR1		
	HR2		
HR Readiness	HR3	4	(Hossain et al., 2017)
	HR4		
	IR1		
	IR2		
Innovation Resistance	IR3		(Kaur et al., 2020)
	IR4		
	IR5		
		5	
	LT1		
	LT2		
Lack of Trust	LT3	4	(Sattu et al., 2024)
	LT4		
	PV1		
	PV2		
Perceived Value	PV3	4	(Sattu et al., 2024)
	PV4		
	RA1		
	RA2		
Relative Advantages	RA3	4	(Puklavec et al., 2018)
	RA4		
	SPC1		
	SPC2		
Security and Privacy	SPC3	4	(Sattu at al., 2024)
Concerns	SPC4		

Pilot Testing

The structured questionnaire, was made on Google Docs and distributed to the selected participants. There were total of 70 respondents and the questionnaire was modified which was purely related to respondents. Feedback was collected on the clarity, relevance, and comprehensiveness of the questions. The responses were analyzed for reliability using Cronbach's alpha to ensure internal consistency. Feedback from participants was also reviewed to identify any issues with the questionnaire.

Table 1: Normality testing for skewness and Kurtosis

	Excess kurtosis	Skewness
AA	3.120	-1.366
CE	3.007	-1.236
HRR	-0.236	-0.414
IR	-0.651	0.461
LT	0.977	0.889
PV	0.639	-0.950
RA	1.176	-0.928
SPC	-0.850	-0.265
UF	2.911	-1.635

Sampling and Data Collection

The data was collected by circulating the questionnaire among the IT and HR professionals of from the IT companies in Pakistan. A total of 70 responses was collected. The survey was based on purposive sampling technique. This technique is also called non-probability sampling. This study had a targeted audience that fit best for the research and people with relevant characterizes and experience were suitable for this study. Not only it saved time but it enabled to gather in-depth data from knowledgeable individuals.

Descriptive Analysis

The research gives a detailed overview of the data by using descriptive analysis, revealing insights into the demographic distribution of respondents as well as the major tendencies and variances of the measured variables. This analysis lays the groundwork for more complex statistical tests and analyses.

The demographic variables defining the attributes and characteristics of the respondents will include age, gender, qualification, work experience and designation. The construct variables will include Adoption of AI, Perceived Value, Cost Effectiveness, Usefulness, Relative Advantages, Lack of Trust, Security and Privacy Concerns, Innovation Resistance and HR Readiness. The tools that will be used for data analysis was Statistical Package for Social Sciences (SPSS). Meanwhile for variable analysis SMART PLS was utilized to run the data received from the respondents.

Assessment of Measurement Model

To assess the quality of our research model, we'll utilize SmartPLS software and its PLS-SEM algorithm. This approach differs from traditional SEM methods in its focus on maximizing analytical power rather than absolute fit.

SmartPLS will guide us through a measurement model assessment. Here, we'll examine the reliability and validity of our constructs also known as latent variables. We'll check for internal consistency termed as Cronbach's Alpha to ensure our measures accurately reflect the underlying concepts. Additionally, convergent validity will be assessed through factor loadings, which indicate how strongly each indicator variable contributes to its respective construct. Finally, discriminant validity will be evaluated to confirm that our constructs are distinct from each other.

Once the measurement model is validated, we'll proceed to run the PLS-SEM algorithm. This algorithm estimates path coefficients, which represent the strength and direction of the relationships between our constructs. These path coefficients will help us understand how changes in one variable i.e independent influence another variable i.e dependent. Additionally, SmartPLS calculates various fit indices to gauge the overall model's explanatory power and predictive capability.

By employing SmartPLS and PLS-SEM, we'll gain valuable insights into the relationships within our research model. This allows us to not only assess the validity of our theoretical framework but also to identify the most impactful factors influencing our dependent variables.

Assessment of Structural Model

After establishing a reliable and valid measurement model, we'll delve into the structural analysis. SmartPLS, with its powerful PLS-SEM algorithm, will be our key tool for this stage.

Here, we'll focus on understanding the relationships between our constructs, specifically how changes in one variable (independent) influence another (dependent). SmartPLS calculates path coefficients, similar to traditional SEM, but with a focus on predictive power. These coefficients will be accompanied by t-statistics, which assess the statistical significance of each path.

To ensure the robustness of our findings, we'll utilize bootstrapping. For each resample, the PLS- SEM algorithm is re-run, generating new path coefficients and t-statistics. This process helps us estimate the sampling distribution of these values and determine their statistical significance with greater confidence.

By analyzing the bootstrapped t-statistics, we can evaluate the strength of evidence supporting our research hypotheses. If the t-statistic for a path coefficient exceeds a critical value, we can conclude that the relationship between the constructs is statistically significant.

In essence, SmartPLS and bootstrapping provide a comprehensive analysis of our structural model. We'll gain insights into the direction and strength of relationships between constructs, along with robust evidence to support (or reject) our proposed hypotheses.

Data Analysis and Results

Respondent Profile

The demographic variables were calculated using the SPSS software. The demographic analysis has been conducted on collected data of respondent's profile which includes, Age, Gender, Education and Experience.

The participant demographics show a diverse distribution in terms of age, gender, education, work experience, and job designations. The age group is varied, with 28.6% of participants aged 18-25, 25.7% aged 26-33, 24.3% aged 34-40, and 21.4% aged 40 and above. Gender distribution is predominantly male at 67.1%, with females comprising 32.9% of the participants. In terms of educational background, 41.4% hold a bachelor's degree, 54.3% have a master's degree, and 4.3% possess a doctoral degree. Participants' work experience ranges from less than a year (10.0%) to over 15 years (20.0%), with the largest group having 1-5 years of experience (40.0%). The job designations reflect a wide range of roles, including HR and IT positions. Notably, HR Managers constitute the largest group at 25.7%, followed by HR Officers and Senior HR Managers at 10.0% each. Other roles include IT Managers (10.0%), IT Officers (8.6%), and various senior and executive positions in both HR and IT departments. This diverse demographic provides a comprehensive view of the participant pool, highlighting a blend of experience levels and professional roles as shown in Table 2.

Table 2: Demographic Profile (n=70)

Demographic Variable	Category	Frequency	Percentage	Cumulative Percentage
Age	18-25	20	28.6%	28.6%
	26-33	18	25.7%	54.3%
	33-40	17	24.3%	78.6%
	40 and above	15	21.4%	100.0%
Gender	Male	47	67.1%	100.0%
	Female	23	32.9%	32.9%
Education	Bachelors	29	41.4%	41.4%
	Masters	38	54.3%	100.0%
	Doctoral	3	4.3%	45.7%
Experience	Less than a year	7	10.0%	100.0%
	1-5 years	28	40.0%	40.0%
	6-10 years	16	22.9%	90.0%
	11-15 years	5	7.1%	47.1%
	15 years and more	14	20.0%	67.1%
Designation	GM HR	1	1.4%	1.4%
	HR Assistant	1	1.4%	2.9%
	HR Associate	1	1.4%	4.3%
	HR Coordinator	1	1.4%	5.7%
	HR executive	3	4.3%	10.0%
	HR lead	1	1.4%	11.4%
	HR Manager	18	25.7%	37.1%
	HR Officer	7	10.0%	47.1%
	HRBP	2	2.9%	50.0%
	IT engineer	1	1.4%	51.4%
	IT executive	3	4.3%	55.7%
	IT manager	7	10.0%	65.7%
	IT officer	6	8.6%	74.3%
	Senior HR Manager	7	10.0%	84.3%
	Senior IT Manager	4	5.7%	90.0%
	Senior Manager HR	4	5.7%	95.7%
	Sr. HR Manager	1	1.4%	97.1%
	Sr. HRBP	1	1.4%	98.6%
	Sr. Manager	1	1.4%	100.0%

Descriptive Statistics Analysis

After the data was collected, some of the data was cleaned and a few values were identified and deleted. This model defines the relationship between variables and items. We can evaluate the measurement model through construct reliability, individual item reliability, conversion validity, and discriminant validity. The hypothesis was tested by regression analysis by PLS SEM on SMART PLS software.

Table 3: Outer Loadings

	AA	CE	HRR	IR	LT	PV	RA	SPC	UF
AA2	0.813								
AA3	0.919								
AA4	0.885								
CE1		0.913							
CE2		0.929							
CE3		0.917							
HRR1			0.848						
HRR2			0.876						
HRR3			0.830						
HRR4			0.831						
IR3				0.909					
IR4				0.965					
LT3					1.000				
PV2						0.823			
PV3						0.936			
PV4						0.911			
RA1							0.916		
RA2							0.917		
RA3							0.894		
RA4							0.887		
RA5							0.927		
SPC1								0.951	
SPC2								0.926	
SPC3								0.913	
UF1									0.880
UF2									0.960
UF3									0.933
UF4									0.933

The variables have Cronbach's Alpha and Composite reliability greater than 0.7 which means that it fulfills the criteria of Straub (1987). If we talk about individual item reliability (also called Loadings), it too has individual reliability greater than 0.7 which means that it fulfills the criteria of Churchill (1979). The loading that is above 0.7 validates the instrument reliability. The convergent validity was assessed via average variance extracted (AVE), thereby variables have minimum 0.50 as a value which fulfills the standard provided by Fornell and Larcker (1981).

Table 3: Construct Reliability and Validity

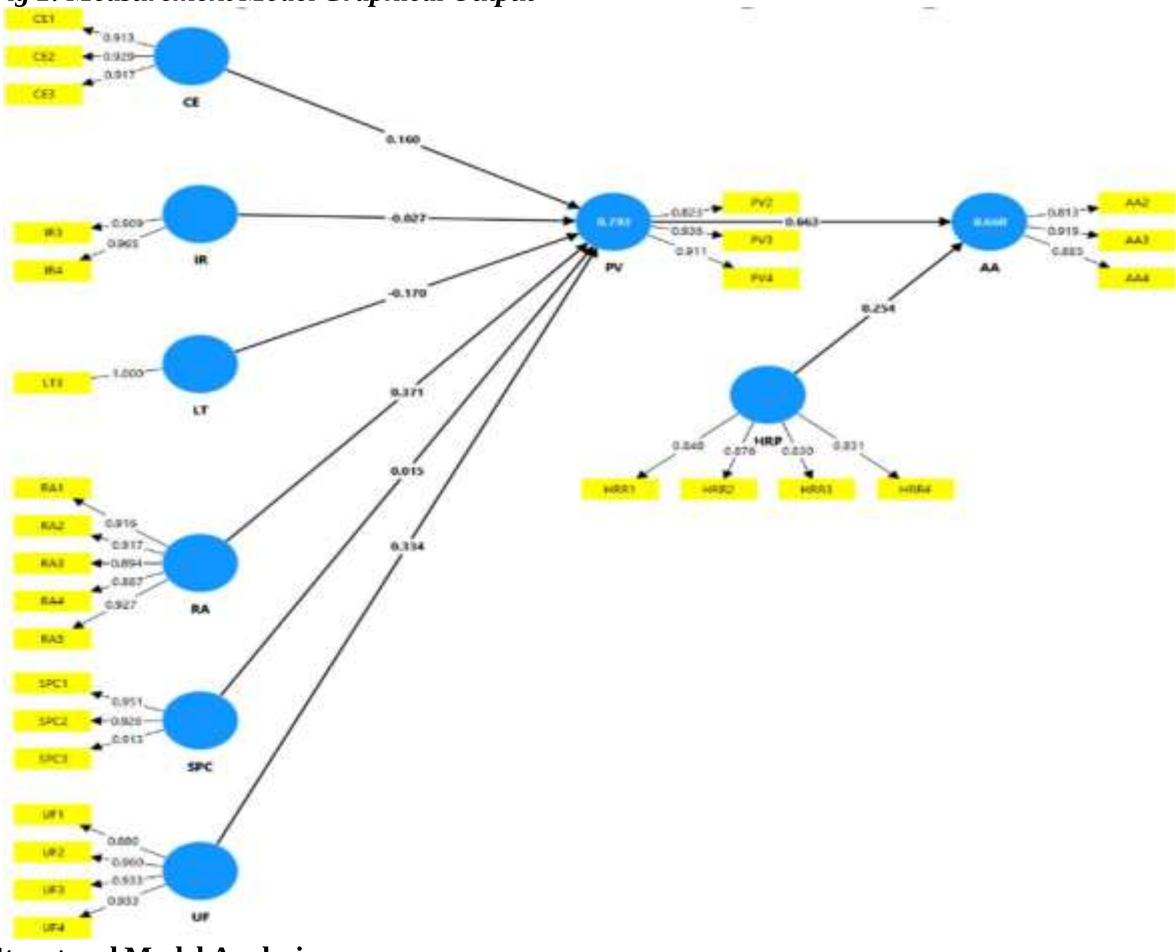
	Cronbach's alpha	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
AA	0.843	0.851	0.906	0.762
CE	0.909	0.911	0.943	0.846
HRR	0.869	0.874	0.910	0.717
IR	0.869	1.007	0.935	0.879
PV	0.869	0.879	0.920	0.794
RA	0.947	0.947	0.959	0.825
SPC	0.922	0.930	0.950	0.865
UF	0.945	0.946	0.961	0.859

The results shows the square root of AVE in the form called diagonal and fulfills the criteria of Fornell and Larcker (1981) i.e. AVE is to be higher than the correlation between the variables which is greater than 0.5. The Heterotrait–monotrait ratio of correlations (HTMT) shows that no HTMT criteria are higher than 0.9 (Gold et al., 2001). As the estimation model affirms the concurrent and discriminant legitimacy, it affirms the variable uniqueness and can be utilized to analyze the primary model.

Table 4: Discriminant Validity

	AA	CE	HRR	IR	LT	PV	RA	SPC	UF
AA									
CE	0.809								
HRR	0.650	0.676							
IR	0.133	0.067	0.116						
LT	0.355	0.377	0.189	0.399					
PV	0.860	0.832	0.529	0.203	0.553				
RA	0.873	0.809	0.675	0.205	0.410	0.887			
SPC	0.420	0.435	0.409	0.088	0.031	0.393	0.456		
UF	0.819	0.763	0.501	0.059	0.383	0.884	0.818	0.369	

Fig 1: Measurement Model Graphical Output



Structural Model Analysis

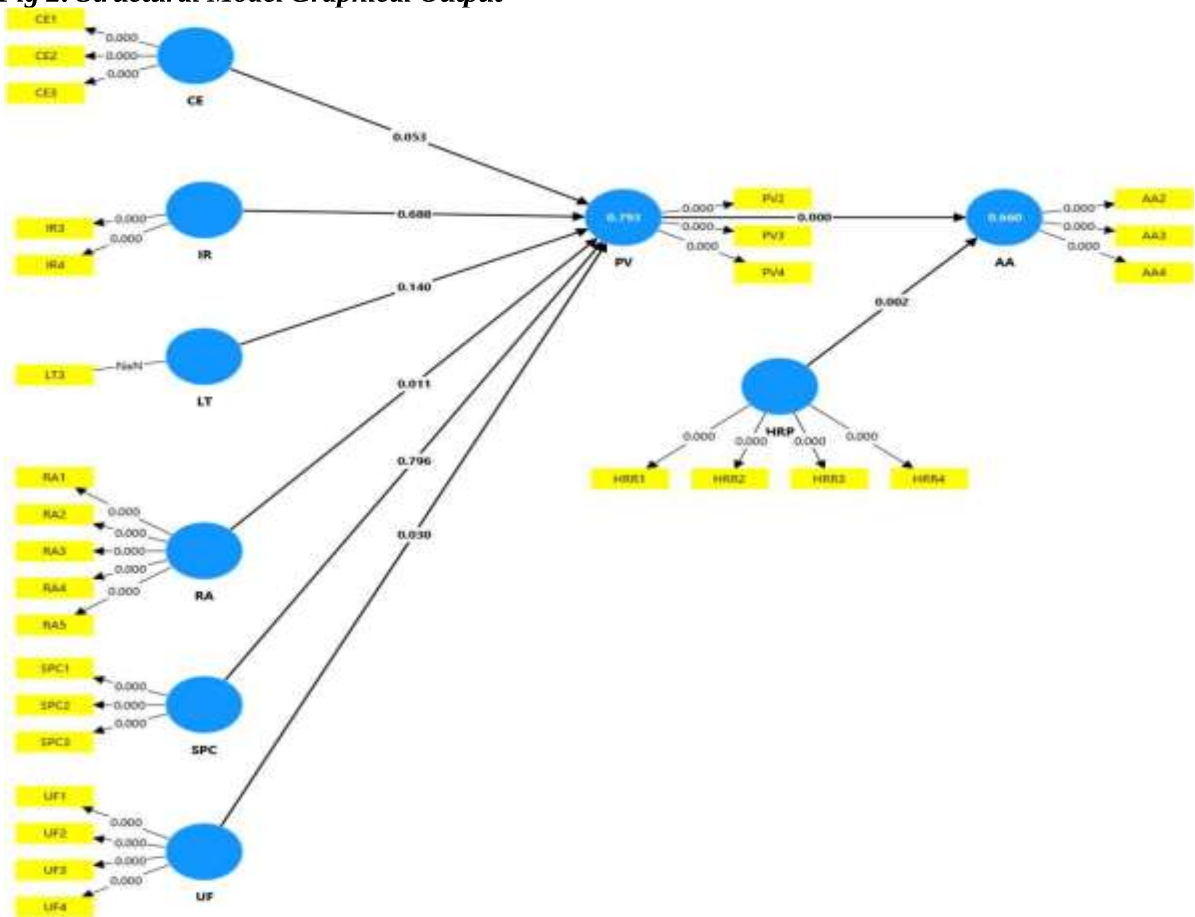
A total of eight hypothesis were developed ranging from H1 to H8 based on the literature review above. Out of eight regression paths, four were accepted which are H1, H3, H7 and H8 and H2, H4, H5 and H6 were rejected. As per the table Relative advantage, Usefulness have a significant impact the perceived value for adoption of AI for talent acquisition in the IT industry of Pakistan. Whereas, Innovation resistance, security and privacy concern, lack of trust and cost effectiveness do not have a significant impact on perceived value for adoption of AI for talent acquisition in the IT industry of Pakistan. However, perceived value significantly influences perceived value for adoption of AI for talent acquisition in the IT industry of Pakistan.

Another part of our research was to determine the effect of moderating variable, which was HR readiness on Adoption of AI. The construct of HR Readiness was analyzed based on available resources in the context of adoption of AI for talent acquisition in the IT industry of Pakistan. Hence, it was deduced that HR Readiness has a moderating effect during the AI adoption process. The below table shows that HRR has a significant influence of Adoption of AI.

The provided data evaluates several hypotheses (H1 to H8) to determine their impact on Perceived Value (PV) and AI Adoption (AA). The beta values, or original sample values (O), represent the strength and direction of the relationships. Hypotheses H1 (RA -> PV) with a beta of 0.371 and H3 (UF -> PV) with a beta of 0.334 are both accepted, as their p-values are 0.011 and 0.030 respectively, indicating statistical significance at the 5% level. Hypothesis H7 (PV -> AA) shows a strong positive relationship with a beta of 0.663 and a highly significant p-value of 0.000. Hypothesis H8 (HRR -> AA) also demonstrates a significant positive relationship with a beta of 0.254 and a p-value of 0.002. Conversely, hypotheses H2 (IR -> PV), H4 (SPC -> PV), H5 (LT -> PV), and H6 (CE -> PV) are rejected due to their p-values of 0.688, 0.796, 0.140, and 0.053, respectively, which are above the 0.05 threshold, indicating a lack of statistical significance. Thus, the accepted hypotheses are H1, H3, H7, and H8 based on their significant p-values, while the others are rejected due to non-significant p-values.

Hypothesis	Path	Original Sample (O)	Sample Mean (M)	T statistics (|O/STDEV|)	P values	Remarks
H1	RA -> PV	0.371	0.369	2.544	0.011	Accepted
H2	IR -> PV	-0.027	-0.037	0.401	0.688	Rejected
H3	UF -> PV	0.334	0.343	2.167	0.030	Accepted
H4	SPC -> PV	0.015	0.020	0.259	0.796	Rejected
H5	LT -> PV	-0.170	-0.155	1.475	0.140	Rejected
H6	CE -> PV	0.160	0.154	1.932	0.053	Rejected
H7	PV -> AA	0.663	0.658	9.116	0.000	Accepted
H8	HRR -> AA	0.254	0.255	3.066	0.002	Accepted

Fig 2: Structural Model Graphical Output



Discussion

This study has incorporated the VAM model and a few constructs of TOE model to understand how valuable people perceive AI adoption to be for Talent Acquisition. This research delves into how Adoption of AI can help businesses transform their Talent Acquisition (TA) processes. It acts like a roadmap for empowering AI marketers, various stakeholders and HR managers, to not only assess the current adoption and practical applications of AI in TA, but also to drive towards the progress of even more effective AI-powered TA technologies (Vedapradha et al., 2023).

According to Puklavec et al., (2018) relative advantage is an important predecessor of information systems, HRIS, business analytics and intelligence adoption. AI also has the potential to speed up the hiring methods as compared to traditional methods of recruiting talent. It includes swift hiring and identification of quality candidates. The study's findings by (Ramesh and Das, 2022) also reveal that relative advantage have a positive impact on perceived value. Hence our hypothesis H1, that Relative Advantage has a positive effect on Perceived Value is supported.

Albert (2019) suggests that there are several factors that contribute to overcoming Innovation Resistance towards Adoption of AI. This can be considered for adopting AI in IT industry within Pakistan. Employee education plays a vital role when it comes to overcome this barrier and HR managers must invest on it (Vedapradha et al., 2024). A well-informed workforce fosters a smoother transition to AI, ultimately leading to a more efficient and effective talent acquisition process. Hence, the hypothesis H2 that Innovation Resistance negatively influences Perceived value is supported.

According to (Landers and Schmidt, 2016) recruiting high quality candidates is a tough task for TA specialists due to multiple reasons existing within the organization, Hence AI tools for recruitment make it easier to do so. Similarly, perceived benefits is a components of perceived usefulness and if the tools are beneficial the HR managers and the stakeholders will be prompted to adapt them. According to (Pillai and Sivathanu, 2020) if AI can help make fair decisions, speed up process and reduce biasness, companies would adapt them. Hence, people would use them in the overall TA process. As a result of these studies the hypothesis H3 that perceived usefulness has a positive influence on Adoption AI is supported.

(Low et al., 2011) have stated in his previous research that when it comes to seeking jobs, people are concerned to use AI based tools as it out their data and privacy on stake. Yadegaridehkordi et al. (2020) findings also confirm that security and privacy concern has a negative impact on adaption information systems in organizations. With the previous literatures above, our hypothesis H4 that Security and Privacy Concerns have a negative influence on perceived value is supported.

Balasubramaniam et al., (2023) researched and concluded that AI can be used in a moral and ethical way to avoid any negative candidate experience. Yet, the lack of trust has been an ever common concern for employees. Not only candidates but HR professionals also have trust issues with the adoption of AI in Pakistan. (Ore and Sposato, 2022) presented a researched and found out that AI is exposed to cyber security risks and are vulnerable to cyber-attacks. This leads to compromised recruitment that slows down the whole process. Based on this our hypothesis H5 that Lack of trust has a negative influence on perceived value is supported.

Just like consumers when they make a purchase decision, organizations weigh the cost of adopting technology within the organization. However, potential risks arises when cost saving is a main focus. Just consumers often associate a product or service's affordability with lower quality or fewer benefits, organizations also do the same for IT adoption. When perceived value reduces due to cost importance, organizations might miss out on the true usefulness of innovative solutions. According to (Rind et al., 2017) even though an Adoption of IT solution offers economic advantages, its perceived value in the eyes of decision-makers could be negatively impacted. Hence our hypothesis H6, that Cost Effectiveness has a negative effect on Perceived Value is rejected.

As evident from Pillai and Sivathanu (2020) research, AI for Talent Acquisition has the ability to analyze resumes, applications, and profiles for skills and qualifications matching job descriptions. This saves considerable amount of time and man power as well as other resources. This justifies our hypothesis H7 that perceived value has a positive influence of Adoption of AI for Talent Acquisition. Although AI has significant benefits, the initial financial outlay is a tough task for some stakeholders of the companies. To bridge this gap, HR department must prioritize concise communication as to how AI can benefit in the long term. Employee training programs and support programs can help them get rid of the anxiety of using new technology and help them become well-informed of AI (Puklavec et al., 2018).

This research also has a moderating variable which is HR Readiness which was a part of a study by (Hossain et al., 2017). If HR departments truly need to capitalize on AI benefits like faster screening, shortlisting and reduced bias, they need to adapt it according to their needs (Pillai and Sivathanu, 2020). Hence our hypothesis H8 HR Readiness has a positive influence on Adoption of AI. HR departments in organizations must come up with a well-defined AI integration plan to seamlessly merge AI with existing recruitment processes. All in all, HR readiness plays a pivotal role in ensuring successful AI adoption and integration within talent acquisition

This research also delves into the factors that affect adoption of AI in the IT industry of Pakistan. The Value Based adoption model is validated through the findings and sheds light on the decision- making process of HR managers. This survey not only contributes to existing knowledge on technology adoption in HR practices, but also talks about the under-researched area of talent acquisition within Pakistan. Furthermore, the findings provide valuable insights into how IT companies in Pakistan can control AI to streamline their recruitment processes. The study goes beyond simply authorizing the practicality of AI adoption; it also emphasizes the importance of HR readiness. This includes ensuring access to necessary resources, providing appropriate training, and prioritizing data privacy.

Results and Recommendation

The surge of AI tools adaption across different industries has caused researchers to delve deep into researches and find the actors that govern their integration within diverse organizational functionalities. This research focused on Talent Acquisition particularly for adoption of AI within the context of Pakistan by using the VAM model to understand how benefits are balanced out with sacrifices during the adoption process. While the trend of AI in talent acquisition is gaining momentum globally, Pakistani IT organizations seem to be lagging behind in fully using its potential.

The study’s findings showed that relative advantage, and usefulness had a positive impact on perceived value and act as the key drivers that enhance the perceived value of AI for talent acquisition. However, concerns around security, data privacy, and a lack of trust in AI vendors were identified as variables that can hinder the perceived value and eventually, successful adoption of AI in Pakistan. Interestingly, the study found that innovation resistance, previously highlighted in other research as a significant factor, had a negative effect in terms of perceived value in our study. Same goes with cost-effectiveness, as previous researchers found that it has a positive correlation with technology adoption but in our research it had a negative influence on adoption of AI.

Even though there are some limitations in the adoption of AI, it has the potential to revolutionize talent acquisition to ensure reasonable, transparent and effective hiring practices. Thus, the VAM model is proven to have greater predictive validity than the other technology adoption models and is well suited to the Pakistani IT sector. However, chances of algorithmic bias, privacy and security issues and innovation resistance demand careful consideration during adoption as mentioned in our research paper. HR and IT managers must work closely with AI developers and data scientists to ensure AI technology’s ethical and responsible use in talent acquisition so that people could easily trust upon it. Thus, our research findings strongly support the proposition that IT executives and HR managers should adopt AI during talent acquisition for both overall hiring and technical hiring. By using AI’s capabilities while navigating its challenges responsibly, IT companies in Pakistan can gain a competitive edge in the recruitment landscape by attracting a talented and diverse personnel. As technology advances, embracing AI in talent acquisition should not be an option but a strategic move in the right direction.

Our research also offers valuable implications for IT and HR professionals who look after technical and overall AI-powered recruitment. Since implementing AI often requires substantial investment, this study equips HR personnel with a framework for evaluating the potential cost-benefit trade- off. The findings serve as a roadmap, helping them identify both the opportunities and potential risks associated with integrating AI-based tools into the hiring process, that too within Pakistan. However, to fully use the power of AI and leverage its capabilities for informed decision-making, professionals may require additional training and familiarization. Ultimately, this study empowers HR managers to strategically incorporate AI-driven talent acquisition into their long-term HR plans, with the goal of optimizing recruitment outcomes. By doing so, companies can achieve benefits like increased efficiency, reduced bias in hiring, and a stronger competitive edge in the talent marketplace all while remaining vigilant regarding potential risks.

The assessment tool i.e VAM model examined in this study assists organizations in evaluating the potential value and advantages of adopting new technologies. Still, the conceptual model primarily focused on financial benefits, such as cost-effectiveness, and did not consider non-financial benefits like customer satisfaction and employee engagement. The studies by future researchers should explore incorporating these non-financial aspects into the perceived benefits analysis. This study also suggests that this model may not be suitable for all types of organizations with straightforward operations and minimal need for cultural or structural adjustments which mostly exist in Pakistan. Nonetheless, in today's increasingly globalized business landscape, many organizations operate with complex workflows and diverse workforces. Future researchers should come up with a more adaptable model that can account for different organizational cultures and the challenges of implementing significant organizational changes. Future research efforts should prioritize the development of such a model, with a particular emphasis on its effectiveness in multicultural settings.

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