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An Empirical Analysis of Factors Influencing AI Adoption in Recruitment and Selection in Pakistan

Rehana Farhat *
Ph.D Scholar at UIMS, PMAS Arid Agriculture University, Rawalpindi, Pakistan.
ranikhalids27@gmail.com
https://orcid.org/0009-0005-6319-8717

Temoor Anjum
Assistant Professor, UIMS, PMAS Arid Agriculture University, Rawalpindi, Pakistan.
https://orcid.org/0000-0002-9534-322X

Muhammad Khalid Sohail
Professor, Department of Accounting & Finance, Bahria Business School, Bahria University, Islamabad, Pakistan.
https://orcid.org/0000-0001-5189-7370

** corresponding author*

Abstract: *Amidst the ongoing competitive challenges in the business environment, AI plays a fundamental role. Despite the pace of AI adoption has shown slow advancement in emerging markets, particularly in Pakistan. Forthcoming years will become essential for organisations to integrate AI into different facets of task management like recruitment and selection (R&S). The core purpose of the research is to address how numerous factors influence the adoption of AI under technology-organisation-environment (TOE) model. The study introduces a basis to examine the importance and interrelationship of key success factors in the adoption of AI. Six key factors influencing AI adoption were derived from a comprehensive review of the literature. The structural model was empirically validated using data collected via a Google-based mail survey conducted in Pakistan. The data is analysed through Structural Equation Modelling, revealing that factors such as relative advantage under Technology factor, technological competency, and support from top-management for Organisational factor, while competitive pressure and vendor support for Environment factor have a significant association with AI adoption regarding R&S in selected firms in Pakistan. The study's findings offer valuable insights for organisations in Pakistan to refine their AI adoption strategies, particularly in R&S, helping them gain a competitive edge. It also highlights key factors specific to the Pakistani context, enhancing understanding of how local dynamics shape AI adoption in HR. These insights can guide organisations in overcoming challenges and optimising AI's potential for organisation success.*

Keywords: *SEM; Pakistan; TOE; factors; recruitment; selection; AI adoption.*

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1. Introduction

The recruitment and selection process is one of the important components of human resource (HR). Artificial Intelligence (AI) is continuously evolving and developing with new capabilities in the context of human resource management (HRM) (Bersin, 2018). The TOE model started with Tornatzky and Fleischer (1990), then was extended by Malik et al. (2021). They suggested a three-way categorisation encompassing technology, organisation, and environment aspects for understanding the adoption of innovative technology.

The technology perspective concerns the characteristics, inventions, or factors like complexity, compatibility, and efficiency. The organisational perspective covers the qualities of HR in an organisation, which includes the structure and adaptability of innovative technologies. The environmental perspective relates to outside of the organisation, like industry, competitors, government rules, and regulations.

In their study of Pan et al. (2021), the TOE model empirically assessed and explored both the driving and limiting factors that can influence AI adoption in R&S. Their study discovered that numerous factors such as technological competence, firm size, industry, relative advantage, regulatory considerations, and complexity under TOE model directly affected AI adoption.

Studies have explored numerous factors shaping the applicability of the TOE model in the context of innovative technology across different sectors. Farhat & Anjum (2024) have explored factors relevant to the TOE model in R&S processes in Pakistan via interviews. Fenwick, Molnar, & Frangos (2024) highlight that HRM can portray a proactive part towards supporting AI integration, ensuring the technological complements rather than replacing human capabilities. Sjöberg and Schill (2023) have identified effective communication as a key facilitative factor, while unease surrounding as the main barrier to innovative technology. Nain and Shyam (2024) examined AI's role in HR hiring, highlighting its ability to streamline applicant screening, reduce unconscious bias, and enhance candidate experience through tools like chatbots. However, challenges like data security and overreliance on technology persist. A balanced approach combining AI efficiency with human judgement is essential.

The key findings of the reviewed studies are presented in Table 1.

Table 1. Key findings

Authors	**Year**	**Main Findings**
Pan et al.	2021	Technological competence, firm size, industry, relative advantage, regulatory considerations, and complexity affected AI adoption.
Sjöberg & Schill	2023	Identified unease surroundings as the main barrier to innovative technology.
Rawashdeh, Bakhit, & Abaalkhail	2022	Technological factors shaped the adoption of AI.
Chen et al	2023	Managerial support & skilled professionals significantly influenced AI adoption.
Hmoud et al.	2023	Numerous factors under the TOE model affected AI adoption
Fenwick, Molnar, & Frangos	2024	HRM can portray a proactive part towards supporting AI integration.
Nain & Shyam	2024	Examined AI's role in HR hiring.
Karan and Angadi	2025	The study reported significant effects of various TOE model factors on AI adoption in India, except for normative pressure in the environmental context.

As indicated by previous research, this study aims to examine multiple factors regarding AI adoption in the R&S process in the context of Pakistan. Firstly, the study will identify the TOE model factors through literature that are more relevant and can affect AI adoption in the context of Pakistan. Secondly, it will empirically examine the effect of relevant TOE model factors on the adoption of AI. Therefore, the study's research questions are:

What factors contribute to the adoption of AI in the R&S process in Pakistan from a technological perspective?

What factors affect the adoption of AI in the R&S process in Pakistan from an organisational perspective?

What factors influence the adoption of AI in the R&S process in Pakistan from an environmental perspective?

2. Literature Review

In the study of Fenwick, Molnar, and Frangos (2024), it has been observed that AI is transforming organisational processes, enhancing their efficiencies, enabling sophisticated data analysis, and contributing to organisational value generation. However, they note that AI adoption and implementation within organisations come with challenges. While data scientists and engineers are skilled in managing data-related tasks, they regularly observe the more nuanced human factors essential for successful AI integration. This is where HRM plays a significant part, acting to ensure the AI implementation that aligns with human values and organisational objectives.

According to Madhavi & Kaveri's (2024) study, they explored how IT firms in Hyderabad use AI, chat platforms, social media, and virtual reality in hiring, as the city emerges as an IT hub. A quantitative survey assessed the impact of these technologies on recruitment, examining how top firms use them to attract talent and the challenges and effectiveness involved.

Similarly, Farhat & Anjum (2024) examined several factors related to the TOE framework in the R&S process through interviews conducted in the context of Pakistan. In their study, the sample consisted of senior management from organisations that have either adopted AI or intend to do so. Their research confirmed several existing factors and identified some new factors. The validated factors affecting AI adoption in the R&S process include the technology perspective (complexity, cost-effectiveness, and relative advantage), the organisational perspective (firm size, technological competence, management support), and the environmental perspective (competitor pressure, AI vendor support) as conceptualised in the TOE framework.

Kapoor (2024) examined barriers towards the adoption of AI in hiring procedures, using the analytic hierarchy process (AHP) to identify key factors. Environmental and organisational barriers were identified as the most significant, along with sub-barriers like competitive pressure, a deficit of government support, and IT infrastructure. The findings offer beneficial insights for HR managers considering AI recruitment solutions.

According to Rawashdeh, Bakhit, and Abaalkhail (2022), technological factors influence AI adoption.The study also examined the mediation effect of accounting automation on it. While in the study of Chen et al. (2023), managerial support and skilled professionals significantly influence adoption intentions, which enable authorities to realistically involve HR analytics. Moreover, their study proposed that immediate adopters and the use of analytical patterns can also be helpful for managers to direct the complex procedures and support the decision-making process.

Samy et al. (2023) examined the influence of applying the TOE model under the contexts of technological (competitive advantage, trust, security, complexity, and compatibility), organisational (performance, technology maturity, readiness, and senior management), and environmental (infrastructure, internet service provider) perspectives. The study focused on how these factors affect informed decision-making, with HRIS serving as a mediating factor.

In contrast, the study of Maroufkhani, Iranmanesh, & Ghobakhloo (2023), the mediation analysis was conducted by using different factors of the TOE model.

According to Balcioğlu & Artar's (2024) study, they examined candidate views on AI-supported chatbots in recruitment, highlighting factors like performance anxiety and comfort. Results showed AI-assisted interviews offer a better experience, suggesting AI's potential to improve recruitment. Ease of use and suitability are key factors in adopting AI tools in hiring strategies.

In another study, Hmoud et al. (2023) examined the key influences of the TOE model that facilitates the implementation of Business Intelligence. Data were collected in Jordan from a sample of managers.

The results of their study indicated that information quality, information culture, organisation readiness, perceived complexity, top managerial support, relative advantage, vendor selection, and compatibility have a noteworthy influence on the adoption of Business Intelligence, while competitor pressure was found to be insignificant. Furthermore, in their study, information culture emerged as the strongest predictor, whereas complexity was found to negatively act as a barrier towards adoption.

According to Neumann, Guirguis, & Steiner's (2022) study, despite its potential, AI adoption in public organisations faces challenges, with limited research on success factors. The study applied the TOE model and revealed that technological and organisational factors vary across adoption stages, while environmental factors are less significant. It deepens understanding of AI adoption dynamics in public contexts.

Further, the study of Phuoc (2022) explored factors influencing AI adoption in Vietnam, identifying ten key factors within the TOE model. The findings showed that technical compatibility, relative advantages, organisational readiness, technical complexity, managerial capability, government involvement, vendor support, and uncertainty significantly affect AI adoption. However, no significant link was found between organisation size and AI adoption.

Researchers have explored AI adoption, application, and management using various theoretical frameworks. The most prominent theory for the organisational level is Diffusion of Innovations (DOI) (Rogers, 1995).

In this study, we utilised the TOE model and the DOI theory as a driving perspective for AI adoption at the organisational level and to further investigate the key determinants. When an organisation initiates innovation, such as adopting AI, resistance often arises, particularly when it disrupts employees' established routines and comfort zones. Adoption, as explained by the TOE framework, is influenced by factors at the organisational level. Moreover, the DOI theory explains the how and why behind innovation uptake, emphasising attributes like relative advantage, compatibility, and complexity. Integrating DOI into TOE enriches the understanding of the technological context, while TOE adds organisational and environmental depth to DOI's individual and social dimensions.

Together, they provide a comprehensive perspective on AI adoption, accounting for both internal readiness and external influences. The selection of the TOE framework is supported by its widespread recognition as a reliable theoretical model in technology management, as established by Hsu, Ray, & Li-Hsieh (2014). Key factors were identified through insights drawn from numerous studies and are illustrated in Figure 1, followed by the formulation of hypotheses.

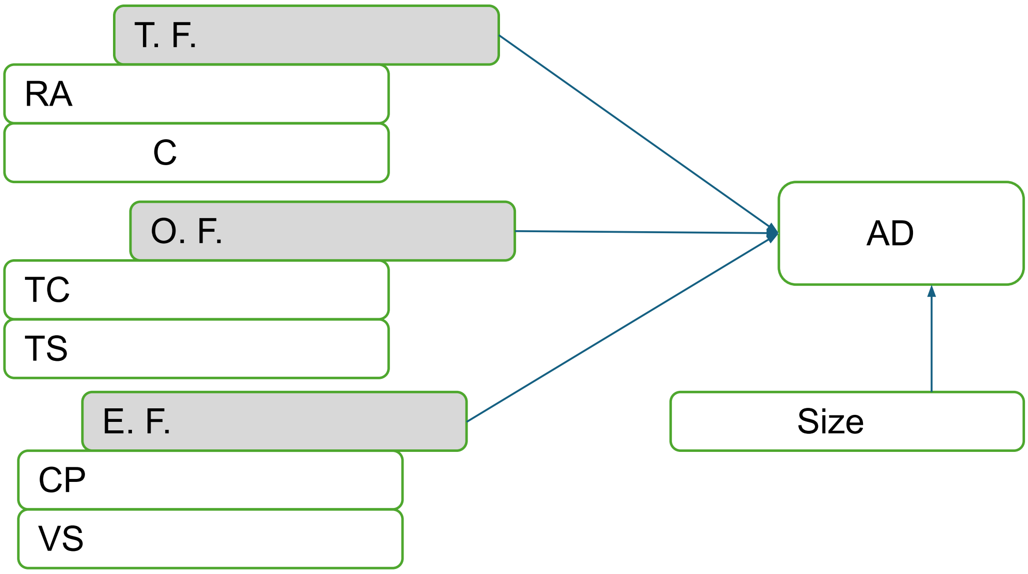

Figure 1. Theoretical diagram; Relative Advantage (RA), Complexity (C), Technological Competency (TC), Top Management Support (TS), Competitor Pressure (CP), AI Vendor Support (VS), Adoption of AI in R&S (AD), Technological Factors (T. F.), Organisational Factors (O. F.) and Environmental Factors (E. F.).

H1(a, b): Relative advantage and complexity underneath the Technology factors of the TOE model influencing decisions to adopt AI in R&S.
H2(c, d): Technological Competence and Top management support underneath the organisation factors of the TOE model influencing decisions to adopt AI in R&S.
H3(e, f): Competitive pressure and AI vendor support, underneath the environmental factors of the TOE model, influencing decisions to adopt AI in R&S.
H4: Size has a significant influence on decisions to adopt AI in R&S.

3. Methodology

To empirically validate the proposed model, we began with a comprehensive review of relevant literature and then employed a quantitative approach to analyse the effect of different factors of the TOE framework on AI adoption. A thorough exploration was conducted of prior studies applying the TOE framework at the organisational level, towards AI adoption in the R&S process. Consequently, to ensure the relevance and clarity of the indicators in assessing the TOE model dimensions for this study, a pre-test survey was carried out.

This part depicts the instrument and the procedure for data collection. To engage a broad range of potential contributors, the study administered a mail survey via a Google Form, targeting companies in Pakistan that use AI in their R&S processes. The survey assessed seven constructs: "Relative Advantage, Complexity, Technological Competency, Top Management Support, Competitive Pressure, AI Vendor Support, and AI Adoption" in R&S, along with company size as a control variable, comprising a total of twenty-three items.

Responses were collected on a 5-point Likert scale, ranging from "Strongly Agree" (5 points) towards "Strongly Disagree" (1 point). Through Google Forms, three hundred emails were sent for a survey focused on senior managers, managers, and senior HR officers, particularly those directly involved in the R&S processes within the selected firms in Pakistan.

In line with the methodology outlined by Hair et al. (2014), 240 responses were received, and the data were carefully reviewed for missing values, inconsistent response patterns, and potential outliers. Following this screening, the number of valid responses was reduced to 210, that is 80 percent response rate which is to be considered adequate for quantitative analysis (Chen, 2017), as the sample size was determined based on SEM guidelines (Hair et al., 2010), which recommend 5 to 10 respondents per indicator. With twenty-three indicators in this study, a minimum of 115 responses was required.

Although the sample is concentrated in three main sectors, banking, telecommunications, and IT, it remains reasonably representative of Pakistan's context, as these sectors lead in AI adoption in recruitment and selection. The variation in organisational size and respondent experience also contributes to the sample's overall representativeness.

While the study offers important insights into AI adoption, the generalisability of the findings may be influenced by potential sampling biases. The sample is largely concentrated within three major sectors in Pakistan, and data were primarily collected from organisations that were more accessible through online platforms and were already engaged in adopting AI in their R&S processes.

In this study, the primary sectors represented include banking (69.52%), telecommunication (10.48%), information technology (11.43%), and other sectors (8.57%), as shown in Table 2. The limited representation of sectors is attributed to the slow pace of AI adoption in R&S practices across organisations in Pakistan.

Table 2. Respondent's Demographics

S#	Sectors	No. of firms	No. of respondents	%age of respondents
1	Banking	21	146	69.52 %
2	Telecommunication	4	22	10.48 %
3	IT	9	24	11.43 %
4	Others	4	18	08.57 %
	Total	38	210	100.00 %

Structural Equation Modelling (SEM) is adequate for investigating the data. SEM is a powerful technique for conducting high-quality multivariate statistical analyses. Smart PLS is employed to evaluate the constructs, both the measurement and structural models.

4. Firm Size

Company size is a widely discussed component in the adoption of innovative technology at the organisational level (Baker, 2011; Oliveira & Martins, 2010). While some research suggests it may not be relevant (Oliveira & Martins, 2010), many studies show that larger companies are more likely to adopt AI, especially in early stages due to resource richness (Rogers, 2003; Hsu, Kraemer, & Dunkle, 2006; Wang et al., 2010; Baker, 2011).

Firm size is measured as a control variable. According to the study of Garrison, Wakefield, & Kim (2015), firm size evaluated through an ordinal scale constructed on employee count: 1 indicates firms with fewer than 500 employees; 2 represents firms with 500–999 employees; 3 corresponds to 1000–1499 employees; 4 to 1500–1999 employees; and 5 to firms with over 2000 employees. Prior research highlights the impact of firm size on the adoption of innovative technology. Larger firms, with more resources, tend to take greater risks in adopting innovations like AI, compared to smaller firms (Thiesse et al., 2011). Accounting for firm size helps minimise variability in AI adoption decisions, particularly in R&S. In this study, firm size is measured as the log of the total number of employees.

5. AI Adoption

Adoption of innovative technology is essential for achievement (Syeda, 2018). AI adoption has been studied at both the organisational and individual perspectives (Oliveira & Martins, 2011). TOE explains how various factors influence technological innovation decisions. Previous studies applying the TOE framework have focused on factors affecting AI adoption, especially in R&S (Farhat & Anjum, 2025; Kushwaha et al., 2020).

6. Technological Context

Technology plays a key role in AI decision-making, with studies examining how innovative characteristics and available technologies influence organisational innovation (Chau & Tam, 1997; Rogers, 1995). While the original TOE model lacked detail on technological factors, later research expanded it by introducing more reliable constructs (Zhu et al., 2006). This study explores technological factors, such as relative advantage and complexity, which have been extensively acknowledged and discussed in previous research (Wang et al., 2010; Zhu et al., 2006).

7. Relative Advantage

AI-enabled learning capabilities offer notable advantages, such as improving customer service through chatbots, speech facilities, and computerised network operations (El Khatib, Al-Nakeeb, & Ahmed, 2019). The integration of AI with large datasets can drive innovation and provide competitive advantages by enhancing service quality, reducing costs, and increasing efficiency. As awareness of these benefits increases, organisations and individuals are more likely to embrace AI, with relative advantage being a key factor driving adoption.

8. Complexity

Complexity represents the challenges to AI adoption, with easier integration increasing the likelihood of AI adoption by organisations (Oliveira et al., 2014). AI's complexity arises from its immaturity, shortage of expertise, and IT specialists, time-intensive processes, and excessive costs. AI immaturity is often considered its greatest challenge. Prior studies specified that IT maturity plays a vital role in firms' decisions to adopt and implement innovative technologies. When technology is mature and firms can collaborate efficiently with vendors, adoption becomes more feasible (Huang & Palvia, 2001). Therefore, complexity is hypothesised to exert a negative relationship with AI adoption.

9. Organisational Context

The organisation context encompasses its characteristics, such as structure, communication processes, size, and internal resource availability (Tornatzky & Fleischer, 1990). Prior studies have used different proxies to assess this factor within the TOE framework (Wang et al., 2010). This study focuses on two commonly used proxies: Technological Competency and Top Management Support, which are crucial for supporting innovation adoption. This expertise is typically unique to the organisation, non-transferable, and deeply embedded within its structure, helping to differentiate the firm from its competitors (Horani et al., 2023)

10. Technological Competency

Technological competency, including technical expertise and collaboration strategies, is critical for integrating innovative technologies like AI. Competency is an essential factor influencing AI adoption (Garrison, Wakefield, & Kim, 2015). Strong technical capabilities help reduce integration challenges, allowing IT departments to implement AI technologies more swiftly and efficiently. Firms that can effectively implementing technical solutions and incorporate innovative technology into their infrastructure are more likely to adopt AI successfully. Consequently, companies with stronger technological capabilities tend to adopt AI successfully.

11. Top Management Support

According to Müller & Jugdev (2012), managerial support is vital for AI adoption. Additionally, Elbanna (2013) highlighted that ongoing and consistent support from management is essential during project implementation, as its absence can result in project failure. Senior managers play a key role by appointing personnel to lead developments and by allocating necessary financial and other resources (Willis & Sullivan, 1984). To ensure a successful AI adoption, managerial support must align with the firm's strategic objectives. Therefore, in this study, Top Management Support is expected to have a positive relationship with AI adoption.

12. Environmental Context

The environmental context includes exterior factors like industry characteristics and competition, which influence organisations. These factors can moreover encourage or delay the adoption of innovative technologies, such as AI, often driven by pressure from governments, competitors, and customers. Environmental context encompasses external factors that affect an organisation, including industry characteristics, regulations, competition, and government interactions (Chau & Tam, 1997). These external elements can present both incentives and challenges for adopting innovative technologies. Companies frequently adopt AI in response to pressures from governments, competitors, and customers (Gibbs & Kraemer, 2004; Tornatzky & Fleischer, 1990). In this study, AI Vendor Support and Competitive pressure are taken as more influential factors of the TOE model affecting the AI adoption.

13. Competitive Pressure

Competitive pressure acts as a significant driver of technological innovation, highlighting the necessity of adopting innovative technologies to sustain market competitiveness (Sumner, 2000). Further, Porter and Millar (1985) argued that IT innovation can revolutionise industry structures and reshape competitive strategies. Embracing these innovations provides firms with new opportunities to outperform their competitors. Ultimately, adapting to competitive pressures is vital for success in today's dynamic marketplace. Firms often adopt innovative technologies to maintain or gain competitive advantages when they see competitors doing the same (Oliveira & Martins, 2008). Therefore, competitive pressure is positively associated with AI adoption.

14. AI Vendor Support

Firms typically lack in-house technical and transformational skills and need to manage innovations like AI, making collaboration with AI vendors essential. Assael (1984) demonstrated that vendor involvement significantly accelerates the adoption and diffusion of innovations. Vendor support has consistently been identified as a critical factor in AI adoption (Sulaiman & Wickramasinghe, 2014). In the AI domain, suppliers play a key role, particularly in providing algorithms and models that are the core elements of AI. Since various organisations lack expertise in these areas, they rely on vendor partnerships to jointly develop AI applications. As a result, vendor support positively influences AI adoption.

15. Results

15.1. Measurement Model

The measurement model evaluates the reliability of individual indicators and assesses the construct's convergent and construct's discriminant validity.

Table 3. Analysis - measurement model (validity and reliability)

Latent variables	Indicators	CR	C-Alpha	Lambdas	AVE
AI Adoption	AD-1			0.7801	
	AD-2			0.8450	
	AD-3	0.8781	0.9171	0.8911	0.711
Relative Adv.	RA-1			0.8312	
	RA-2			0.7042	
	RA-3	0.7770	0.8980	0.6570	0.5410

Complexity	C-1			0.7491	
	C-2			0.8311	
	C-3			0.8620	
	C-4	0.8910	0.8171	0.8321	0.6701
Tech. Competence	TC-1			0.7781	
	TC-2			0.7980	
	TC-3	0.8361	0.7431	0.8041	0.6320
Top Mgt. Support	TS-1			0.7731	
	TS-2			0.8011	
	TS-3			0.8210	
	TS-4	0.8820	0.9061	0.8301	0.6540
Competitor Pressure	CP-1			0.7890	
	CP-2			0.6760	
	CP-3	0.7851	0.7890	0.7551	0.5510
AI Vendor Support	VS-1			0.8141	
	VS-2			0.8311	
	VS-3	0.8452	0.8571	0.7620	0.6430

This model is intended to measure seven latent constructs (factors) and one control variable: firm size. Factor analysis is subsequently carried out to identify and validate the indicators linked to each construct related to AI adoption in the R&S process. The findings from the confirmatory factor analysis demonstrate that all pathways between the indicators and the constructs are highly statistically significant. Fornell & Larcker (1981) highlight that the percentage of variance extracted serves as an indicator of the model's construct validity. Each indicator accounts for between 50% and 80% of the total variance explained. Table 3 presents Cronbach's alpha (CA) values, composite reliability (CR) (rho c), and AVE for each construct, along with factor loadings for all corresponding indicators.

All values are above the widely accepted threshold of 0.7 (Kline, 2013). Composite reliability (CR) was used to assess the internal consistency of the scales, offering a more precise measure of reliability (Chin & Gopal, 1995). A CR value of 0.7 is recommended as the minimum standard for ensuring sufficient model reliability (Gefen, Straub, & Boudreau, 2000). The CR values for all constructs meet the threshold.

In Table 3, factor loadings of the majority of indicators are greater than 0.7 and significant, however, two indicators show factor loadings greater than 0.65 and significant. Nevertheless, the AVE of each construct is greater than the threshold of 0.50, which proves convergent validity.

Convergent validity is commonly evaluated through factor loadings and the Average Variance Extracted (AVE). In this study, all AVE values exceed the recommended cutoff of 0.50 (Fornell & Larcker, 1981). Moreover, all computed standard loadings (lambdas) are significant and surpass the minimum threshold of 0.50 (Chin & Marcolin, 1995). Thus, the model's measurements exhibit strong convergent validity.

For discriminant validity, Fornell and Larcker, cross loadings, and Heterotrait-Monotrait ratio (HTMT) are usually used; however, here, the first and last criterion out of three are utilised to evaluate discriminant validity. The Fornell-Larcker criterion is commonly employed. For the first criterion, “the square root of the Average Variance Extracted (AVE) for each construct should be greater than the correlations with other constructs” (Fornell & Larcker, 1981). As indicated in Table 4, the square root of the AVE for each latent construct, highlighted in bold along the diagonal, surpasses the correlations among the latent constructs in the respective rows and columns, thereby confirming their discriminant validity.

Moreover, the correlations between items remain below 0.90 (Bagozzi, Yi, & Phillips, 1991), indicating that the constructs are distinct from one another. Although some constructs show slightly lower levels of construct validity, the majority meet acceptable standards for validity and reliability. As a result, the validity and reliability of the model's constructs are strongly supported.

Table 4. Fornell-Larcker for Discriminant Validity

onstructs							
I Adoption	**.8402**						
Relative adv	.0581	**.7341**					
Complexity	0.3111	.3221	**.8201**				
Tech. Competence	.4391	.3211	0.0931	**.7931**			
Top Mgt. Support	.1791	.2841	0.4391	.0121	**.8071**		
Competitor Pressure	.5022	.5612	0.5281	.2091	.3691	**.7421**	
AI Vendor Support	.2461	.2562	0.5413	.0025	.4491	.7044	**.8032**

15.2. Hypothesis Testing (Structural Model)

Prior to conducting structural model analysis to observe the relationships of factors with the AI adoption, the reliability and validity of the constructs were confirmed through the measurement model analysis. Analysis was made by applying Partial Least Squares Structural Equation Modelling (SEM-PLS), where the relationships between the IVs and DVs are observed. As shown in Table 5, hypotheses (H1a, H2a, H2b, and H3b) are highly significant as p-values are less than 0.01, while H3a is at the 10% significance level. However, in this study, H1b and H4 are found to be statistically insignificant.

Within the Technology factor of the TOE model, the relative advantage positively affects AI adoption. This study's results support the earlier studies of Pillai and Sivathanu (2020) and Pan et al. (2021) that relative advantage influences AI adoption, as shown and confirmed in H1a. Incorporating AI into the R&S process enables HR professionals to identify the most suitable candidates, enhancing decision-making. It also accelerates the selection process and provides greater control than traditional recruitment methods.

Complexity under the Technology factor of the TOE model remains an imperative determining factor that affects AI adoption, which has usually had a negative impact in the past studies. Consequently, complexity endures, linked to the experience of change that leads to anxiety and annoyance (Oliveira, Thomas, & Espadanal, 2014). Additionally, the complexity of AI stems from its infancy, deficiency of technological expertise and IT specialists, time-consuming processes, and extraordinary expenditures. However, although the sign of the coefficient is negative, but is insignificant as the p value is greater than 0.05, as shown in H1b. Therefore, the findings of this study do not support previous studies of Pillai and Sivathanu (2020), Pan et al. (2021), Chen, White, and Hsieh (2020) that complexity has a negative and significant impact on AI adoption.

However, Karan and Angadi (2025) reported significant effects of various TOE model factors on AI adoption in India, except for the normative pressure factor under the environmental context. The current study's findings are consistent with theirs, as complexity was found to be insignificant within the technological context of the TOE model in Pakistan. These variations suggest that TOE model factors may influence AI adoption differently across countries, depending on their unique adoption dynamics.

Table 5. Results of the Structural Model

	O	M	STD	t	P values
RA->AD	0.3271	0.3231	0.0670	4.8731	0.0000
C->AD	0.0501	-0.0080	0.0750	0.6722	0.2510
TC->AD	0.2090	0.2041	0.0720	2.8850	0.0020
TS->AD	0.0940	0.0910	0.,0341	2.7570	0.0030
CP->AD	0.0870	0.0940	0.0651	1.3381	0.0910
VS->AD	0.1810	0.1790	0.0651	2.7672	0.0031
S->AD	0.0740	0.0800	0.0750	0.9930	0.1604

O denotes Original Sample, M denotes Sample mean, and STD denotes standard deviation.
t statistics are calculated as |O/STD|.

Under the organisational factor of the TOE model, technological competency significantly and positively affects AI adoption. Technology competence refers to intangible assets, such as technical knowledge and some tangible assets, readiness of existing internal technological resources, which are helpful in innovation (Zhu et al., 2006).

As stated by Rogers (2003), technological resources refer to the existing infrastructure, experience, and expertise that support the implementation of innovations without the need for additional investments. The results of this study align with prior research, reinforcing that technological competence is a key factor in facilitating AI adoption (Pan et al., 2021; Zhu et al., 2006; Ransbotham et al., 2017). Hence, we anticipate that technological competence will lead to increased AI adoption in the R&S process, as confirmed in H2a. Prior knowledge enhances absorptive capacity, which in turn motivates companies towards innovation (Cohen & Levinthal, 1990). Consequently, technological competence enables companies to effectively integrate innovative technologies (Garrison, Wakefield, & Kim, 2015).

Top management support, as part of the organisational factor of the TOE model, significantly and positively affects AI adoption, as evidenced by H2b, which this study supports. Likewise, consistent with other studies in the past, the results of this study support previous findings (Ifinedo, 2011; Leach, 2021). Top management endorses AI adoption, recognising that acquiring talent is a significant challenge in today's environment and that AI must be utilised to address this issue.

Under the environment factor of the TOE model, competitive pressure affects AI adoption significantly and positively, as shown in H3a, which is supported in this study. Under external environmental factors, competitive pressure has a positive impact on AI adoption in the R&S process (Alam et al., 2016), supporting H3a. Many firms face significant challenges in attracting and hiring talent, with intense competition in the industry (Beechler & Woodward, 2009). As AI improves recruitment processes across industries (Tong & Sivanand, 2005), organisations feel compelled to adopt AI to remain competitive. Therefore, competitive pressure drives the need for AI adoption in R&S.

Under the environment factor of the TOE model, vendor support affects AI adoption significantly and positively, as shown in H3b, which is supported in this study. Vendor support plays a fundamental role in the AI adoption in the R&S process. As an innovative technology, AI requires guidance throughout both the adoption and implementation phases (Alam et al., 2016), validating H3b. Continuous vendor support, including comprehensive training, is vital to ensure a smooth and efficient AI adoption and usage process.

Company size did not affect AI adoption in this study, as the p-value exceeded the 5% significance level. As a result, hypothesis H4 is not supported. These findings align with the study by Oliveira & Martins (2010), Phuoc (2022), and Trang et al. (2024), which indicate that organisational size does not significantly influence the AI adoption process.

16. Conclusions

In this study, the impact of various factors on AI adoption in the R&S process was analysed under the umbrella of the TOE model in Pakistan. The study is based on primary data collected through questionnaires from the different levels of management in selected sectors where management uses AI in the R&S process. The study documented the positive impact on the R&S process for firms using AI. The study highlights the context of the organisational level, where innovative factors that impact AI adoption are analysed. The findings validate the TOE model and DOI theory in explaining AI adoption framework in the R&S process in selected sectors of Pakistan. However, this study fails to capture the effect of complexity and size of the firm on AI adoption. Nonetheless, all other important factors of the TOE model were found to be significant and impactful on AI adoption.

The study's findings can be beneficial for organisations in Pakistan refining their strategies towards AI adoption and helping them to gain a distinctive and competitive edge in a challenging business environment, especially in the R&S domain.

The generalisability of the results is limited to the three main sectors studied. However, organisations operating in similar sectors from other countries with dynamics not significantly different from those in Pakistan may also find the findings applicable.

One limitation of the study is the relatively small sample size, with only 210 valid responses. Further data is collected from different limited sectors. Only six factors are analysed under the TOE model. Limitations of this study can be addressed in future research by enhancing the sample size, and higher-order constructs can be used for different factors. The role of social networks and employer branding is also important in the R&S process, as these variables use AI techniques, therefore, these elements can be taken into future research.

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