Factors Affecting the Adoption of AI in Recruitment & Selection: An Empirical Study in Pakistan

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ABSTRACT

This study will unveil the effect of different factors on adoption of Technology (AI) in the field of HR specially in recruitment under the technology, organization and environment outlook. SEM is used in this research. There are many factors that can affect the use of AI; however six important factors are selected in this study. The data is collected through questionnaires. Factors such as complexity, competitive advantage under Technology, organizational readiness, and senior management support for Organizational, while competitive pressure and vendor partnership for Environment are found to significantly affect the use of AI technology in recruitment. The study's findings can help organizations in Pakistan to address challenges in today's environment, particularly in recruitment, by leveraging AI technology. Adopting AI can provide significant advantages, enabling these organizations to gain a competitive edge.

Keywords: *Recruitment, AI Technology, SEM*

INTRODUCTION

The TOE model, first introduced by Tornatzky and Fleischer in 1990, was further developed by Malik, Chadhar, et al. in 2021. They outlined a three-dimensional framework that considers technological, organizational, and environmental factors in the adoption of innovative technologies. Pan, Froese, Liu, Hu, and Ye (2022) empirically tested the TOE model, identifying key drivers and barriers to AI adoption in recruitment and selection. Factors like technological competence, firm size, industry, relative advantage, regulations, and complexity significantly influenced adoption of AI technology.

Bazrkar, Moradzad, & Shayegan (2024) study examining AI adoption in Iran's furniture industry recruitment processes, this study surveyed 250 managers using structural equation modeling with Smart PLS. Technological, organizational, and environmental factors significantly impact adoption, enhancing recruitment efficiency, reducing costs, and mitigating bias through AI tools like applicant tracking systems. Fenwick, Molnar, and Frangos (2024) stress the importance of Human Resource Management (HRM) in driving the seamless integration of AI within organizations. They highlight that HRM should focus on leveraging AI to augment human capabilities rather than replacing them. By aligning AI adoption with both organizational objectives and workforce needs, HRM can create a synergistic environment where technology and human expertise complement each other effectively. Samy, Aziz, Tarek, and Ismail (2023) examined the application of the TOE model across technological (competitive advantage, trust, security, complexity, and compatibility), organizational (performance, technology maturity, readiness, and senior management), and environmental (infrastructure, internet service provider, etc.) dimensions. Their study highlighted how these factors influence informed decision-making, with Human Resource Information Systems (HRIS) acting as a mediating factor.

Building on previous research, this study aims to explore various factors influencing AI adoption in the recruitment within the context of Pakistan (Bazrkar, Moradzad, & Shayegan, 2024; Daoud, & Kammoun, 2024; Hatoum, & Nassereddine, 2024; Jingjing, & Idris, 2024; Khan, Khan, & Aslam, 2024; Mohammed, Al-Okaily, Qasim, & Al-Majali, 2024; NGUYEN, NGUYEN, & DANG, 2022; Revillod, 2024; Siradhana, & Arora, 2024; Wang, Gao, & Zhang, 2024; Wang, Jiang, Han, Zhou, & Li, 2024; Wang, Li, Zhao, Wang, & Xiao, 2024; Yadav, & Kapoor, 2024). The primary research question of this study focuses on examining six key TOE factors that impact the adoption of AI technology across different firms in Pakistan.

LITERATURE REVIEW

Researchers have explored AI adoption, application, and management using various theoretical frameworks. The most prominent theory for organizational level is DOI Diffusion of Innovations (Rogers, 1995). According to Siradhana & Arora (2024) With the rapid growth of AI in modern economies, HR managers increasingly use AI tools for tasks like workforce planning and retention. This study, based on the TOE framework and trust factor, surveyed 615 ITeS companies using PLS-SEM. Key drivers such as cost-effectiveness, top management support, and HR readiness facilitate AI adoption, while challenges like security concerns and technological complexity hinder it. Reliability and credibility enhance HR managers' trust, offering insights for AI integration in HR management. While in the study of Yadav & Kapoor (2024), AI shows promise in HRM but remains under-researched. Using the TOE model and transaction cost theory, this study surveyed 296 organizations to analyze AI adoption in recruitment. While complexity acts as a barrier, technological competency and regulatory support drive adoption. Factors like organizational size and industry type have minimal influence, with transaction costs moderating the key adoption determinants.

Khan, Khan, & Aslam (2024) study explores AI adoption intentions in HRM using the TOE-TAM model, analyzing data from 329 HR professionals in India with Smart PLS v.4. Perceived ease of use significantly influences perceived usefulness, which drives adoption intentions. Relative advantage and HR readiness are identified as critical factors, providing insights into AI adoption in India's HR context.Bazrkar, Moradzad, & Shayegan (2024) study examining AI adoption in Iran's furniture industry recruitment processes, this study surveyed 250 managers using structural equation modeling with Smart PLS. Technological, organizational, and environmental factors significantly impact adoption, enhancing recruitment efficiency, reducing costs, and mitigating bias through AI tools like applicant tracking systems. Revillod (2024) investigated AI recruitment system adoption in Swiss organizations, this study surveyed 324 HR professionals. Key drivers include technological expertise, competitive pressure, and an innovative climate. Public-sector organizations exhibit hesitancy, but active HR involvement and a supportive organizational climate can alleviate resistance. The findings aid understanding of emerging HR information systems diffusion.

Wang et al. (2024) used the TOE framework, this study examines open government data-driven innovation in 236 Chinese firms. Top leadership support boosts innovation capacity, with mediators like technical competence and organizational structure. The findings guide enhancing OGD-driven innovation strategies. Daoud & Kammoun (2024) study analyzes e-commerce adoption in Tunisian SMEs using the TOE framework. A survey of 60 managers found IT vendor support, CEO innovativeness, and customer pressure as drivers, while technological complexity hinders adoption. Machine learning models outperform logistic regression in predicting adoption. Wang, Gao, & Zhang (2024) investigated industrial internet adoption in 314 Chinese SMEs, this study highlights how TOE factors drive digital transformation, boosting performance and competitiveness through integration and innovation. Insights are offered for policymakers and businesses pursuing digital transformation. Mohammed et al. (2024) study examines business intelligence and analytics (BIA) adoption in Jordanian banks using the TOE framework and PLS-SEM. Data from 277 employees reveal technological, organizational, and environmental factors as key drivers, moderated by employees' work experience. The study advocates a holistic approach to enhance BIA utilization.

Jingjing & Idris (2024) Focused on post-adoption e-commerce usage, this study uses the TOE framework to evaluate cross-border e-commerce (CBEC) in Hebei Province SMEs. A pilot survey tested reliability and validity, offering strategies to improve CBEC competitiveness for SMEs, employees, and policymakers. While, Hatoum & Nassereddine (2024) Applied the TOE framework, this study identifies 23 decision-making factors for technology adoption in the construction industry. It reviews trends, proposes 97 evaluation measures, and emphasizes the importance of organizational factors in driving technology adoption under Construction 4.0 advancements. However, Wang, Li, Zhao, Wang, & Xiao (2024) examined digital transformation in Chinese media companies, this study uses the TOE-I framework with machine learning to analyze data from 2010–2020. Environmental factors emerge as the strongest predictors. Recommendations include focusing on policy, economic benefits, and digital talent to facilitate transformation.

Based on all these lates study the main six factors are selected under TOE supported by DOI theory as explained in following framework.

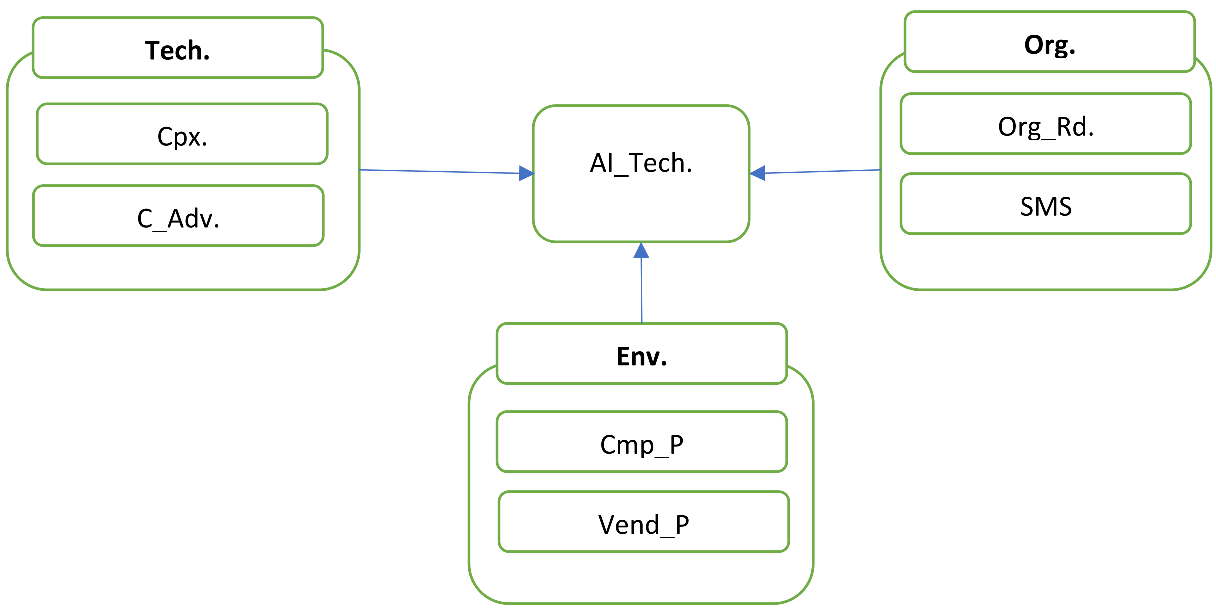

Figure 1. Schematic diagram: AI Technology Adoption (AI_Tech), Complexity (Cpx), Competitive Advantage (C_Adv), Organization Readiness (Org_Rd), Senior Mgt. Support (SMS), Vendor Partnership (Vend_P), Competitor Pressure (Comp_P)

H1(a, b): C_Adv and cpx (Technology) effect on AI_Tech. in recruitment.

H2(c, d): Org_Rd and SMS (Organization) effect on AI_Tech. in recruitment.

H3(e, f): Cmp_P and Vend_P (Environment) effect on AI_Tech. in recruitment.

METHODOLOGY

To validate the proposed model, data was collected via questionnaires from selected firms utilizing AI in recruitment. The survey evaluated six independent variables: Competitive Advantage, Complexity, Organizational Readiness, Senior Management Support, Competitive Pressure, and Vendor Partnership, with AI Technology Adoption as the dependent variable, comprising 22 items in total. Data was gathered using a 5-point Likert scale, targeting HR managers directly involved in recruitment processes in Pakistan. A total of 221 out of 320, fully completed responses were received. Structural Equation Modeling (SEM) was conducted using Smart PLS to analyze both measurement and structural models.

Business success is significantly influenced by the adoption of innovative technologies, particularly artificial intelligence (AI) (Syeda, 2018). This relationship is effectively explained through the TOE (Technology-Organization-Environment) framework. To assess AI technology adoption (AI_Tech), this study utilized the scale developed by Hsu et al. (2006).

For technological factors such as Complexity (Cpx) and Competitive Advantage (C_Adv), scales from Autry et al. (2010) were employed. Organizational factors, including Organization Readiness (Org_Rd) and Senior Management Support (SMS), were measured using scales from Nguyen, Nguyen and Dang (2022) and Alam et al. (2016). Similarly, for environmental factors like Vendor Partnership (Vend_P) and Competitor Pressure (Comp_P), scales from Alam et al. (2016) were also utilized.

Based on prior research, the following relationships and their expected directions have been hypothesized in Table-1.

Table 1: Expected Sign (Relationship) of Constructs

S. No.	Hypothesis	Expected Sign (Relationship)
1	C_Adv->AI_Tech	Positive Sign
2	CPX->AI_Tech	Negative Sign
3	Org_Rd->AI_Tech	Positive Sign
4	SMS->AI_Tech	Positive Sign
5	Cmp_P->AI_Tech	Positive Sign
6	Vend_P->AI_Tech	Positive Sign

AI Technology Adoption (AI_Tech), Complexity (Cpx), Competitive Advantage (C_Adv), Organization Readiness (Org_Rd), Senior Mgt. Support (SMS), Vendor Partnership (Vend_P), Competitor Pressure (Comp_P)

ANALYSIS AND RESULTS

The Measurement Model

The results of measurement model are displayed in table 2. The factor loadings of all majority constructs are meeting the benchmark of 0.7 or greater, however, 4 indicators do not meet the criteria, but as AVE is greater than 0.5, so it can be ignored for the three indicators. The reliability of each construct is validated through construct reliability (CR), and Cronbach's alpha (C_Alpha). values, While for convergent validity is verified through factor loadings and AVE. The values regarding construct reliability (CR), and Cronbach's alpha (C_Alpha) of each construct meeting the benchmark of 0.7 or greater, which proves the reliability as indicated in the study of (Kline, 2013). Theses two measures are considered to be best one for internal consistency of the scales (Chin & Gopal, 1995, Gefen et al., 2000).

Table 2: Reliability and Convergent Validity

Constructs	Indicators	F_Load.	C_Alpha	C_R	A.V.E
	AI_Tech1	0.7274			
	AI_Tech2	0.7580			
AI_Tech	AI_Tech3	0.8294	0.9032	0.8160	0.5972
	C_Adv1	0.7850			
	C_Adv2	0.6971			
C_Adv	C_Adv3	0.6553	0.8371	0.7568	0.5105
	CPX1	0.7045			
	CPX2	0.7558			
	CPX3	0.8273			
CPX	CPX4	0.7574	0.8401	0.8470	0.5814
	Org_Rd1	0.6991			
	Org_Rd2	0.7885			
Org_Rd	Org_Rd3	0.7186	0.7022	0.7799	0.5423
	SMS1	0.7411			
	SMS2	0.7928			
	SMS3	0.7608			
SMS	SMS4	0.8248	0.8924	0.8616	0.6092
	Cmp_P1	0.7301			
	Cmp_P2	0.6921			
Cmp_P	Cmp_P3	0.7004	0.7772	0.7506	0.5009
	Vend_P1	0.7688			
	Vend_P2	0.7531			
Vend_P	Vend_P3	0.7415	0.8457	0.7986	0.5693

AI Technology Adoption (AI_Tech), Complexity (Cpx), Competitive Advantage (C_Adv), Organization Readiness (Org_Rd), Senior Mgt. Support (SMS), Vendor Partnership (Vend_P), Competitor Pressure (Comp_P), Composite Reliability (C_R), Cronbach's alpha (C_Alpha), Factor Loadings (F_Load)

For Convergent validity the most common approach through factor loadings and Average Variance Extracted (AVE). In this case, all AVE values are above the recommended cutoff of 0.50 (Fornell & Larcker, 1981). Moreover, all standardized loadings (λ) are significant and exceed the minimum threshold of 0.50 (Chin & Marcolin, 1995). These results indicate robust convergent validity for the model.

Under measurement model, the analysis of discriminant validity is displayed in table 3. Discriminant validity is typically assessed using the Fornell-Larcker criterion, cross-loadings, and the Heterotrait-Monotrait ratio (HTMT).

In this study, only first criteria was applied. According to the Fornell-Larcker criterion, "the square root of the Average Variance Extracted (AVE) for each construct should exceed the correlations with other constructs" (Fornell & Larcker, 1981).

As shown in Table 3, the square root of the AVE for each latent construct, highlighted in bold along the diagonal, is greater than the corresponding correlations in the rows and columns, thereby confirming discriminant validity.

Table 3: Fornell-Larcker Test Analysis

Constructs	1	2	3	4	5	6	7
AI_Tech	**0.7728**						
C_Adv	0.0622	**0.7145**					
CPX	-0.2932	0.3334	**0.7625**				
Org_Rd	0.3988	0.3402	-0.1189	**0.7364**			
SMS	0.2001	0.2521	-0.3521	0.0245	**0.7805**		
Cmp_P	0.5207	0.5154	-0.6214	0.1721	0.3152	**0.7077**	
Vend_P	0.2045	0.2458	-0.6107	0.0145	0.4921	0.6521	**0.7545**

AI Technology Adoption (AI_Tech), Complexity (Cpx), Competitive Advantage (C_Adv), Organization Readiness (Org_Rd), Senior Mgt. Support (SMS), Vendor Partnership (Vend_P), Competitor Pressure (Comp_P)

Results of Hypotheses Testing under Structural Model

After the analysis of measurement model, where reliability and validity of indicators/constructed was established, now in turn, here, in this section the analysis of hypothesis tested are carried out under structural model. The analysis was conducted using SEM-PLS to examine the relationships between the independent variables (IVs) and dependent variables (DVs). As presented in Table 4, the hypotheses H1a (C_Adv → AI_Tech), H2a (Org_Rd → AI_Tech), H2b (SMS → AI_Tech), and H3b (Vend_P → AI_Tech) are highly significant, with p-values below 0.01. Additionally, H3a (0.421, 0.0042) is significant at the 10.05% level, while H1b (CPX → AI_Tech) is significant at the 0.01 level.

Under the Technology factor, competitive advantage positively influences AI Technology adoption with beta value of 0.3081 and $p<.001$. This study aligns with earlier findings by Pakistan (Bazrkar, Moradzad, & Shayegan, 2024; Daoud, & Kammoun, 2024; Hatoum, & Nassereddine, 2024; Jingjing, & Idris, 2024; Khan, Khan, & Aslam, 2024; Mohammed, Al-Okaily, Qasim, & Al-Majali, 2024;) confirming the impact of competitive advantage on technology adoption. AI in recruitment enhances decision-making, streamlines candidate selection, and provides greater control over traditional methods.

Complexity is one the other main determent of technology adoption often effect negatively, as highlighted in past studies. It is associated with perceptions of change that can cause anxiety and frustration (Hatoum, & Nassereddine, 2024; Jingjing, & Idris, 2024; Khan, Khan, & Aslam, 2024; Mohammed, Al-

Okaily, Qasim, & Al-Majali, 2024; Wang, Jiang, Han, Zhou, & Li, 2024; Wang, Li, Zhao, Wang, & Xiao, 2024; Yadav, & Kapoor, 2024). AI complexity stems from its immaturity, limited expertise, time-consuming processes, and high costs. However, in this study, while the coefficient for complexity is negative, it is statistically significant at 10% level as ($p <= 0.10$).

.**Table 4: Structural Model (Results)**

	Original Sample (O)	Sample mean (M)	STDEV	T statistics (|O/STDEV|)	**P values**
C_Adv->AI_Tech	0.3081	0.3071	0.0687	4.487	**0.0000**
CPX->AI_Tech	-0.0697	-0.0495	0.0398	1.752	**0.0921**
Org_Rd->AI_Tech	0.2181	0.2101	0.0780	2.798	**0.0031**
SMS->AI_Tech	0.1021	0.1011	0.0422	2.421	**0.0042**
Cmp_P->AI_Tech	0.0721	0.0725	0.0387	1.863	**0.0501**
Vend_P->AI_Tech	0.1624	0.1602	0.0720	2.256	**0.0054**

AI Technology Adoption (AI_Tech), Complexity (Cpx), Competitive Advantage (C_Adv), Organization Readiness (Org_Rd), Senior Mgt. Support (SMS), Vendor Partnership (Vend_P), Competitor Pressure (Comp_P)

Another important factor is support from senior management usually effect positively, and in this study also influences Technology adoption. From an organizational perspective, this support is a key driver of AI adoption, aligning with previous research (Jingjing, & Idris, 2024; Khan, Khan, & Aslam, 2024; Mohammed, Al-Okaily, Qasim, & Al-Majali, 2024; NGUYEN, NGUYEN, & DANG, 2022; Yadav, & Kapoor, 2024). “Senior management support recognizes the challenges of talent acquisition in today's environment and advocates for leveraging AI to address these issues effectively”. Hypothesis H2b support this factor as beta is 0.1021 with $p<0.01$, showing highly significant impact.

Organizational readiness refers to the “organization’s preparedness in terms of culture, resources and infrastructure to adopt and implement AI”. In the same way organizational readiness also influences technology’s adoption in recruitment as result can be in Hypothesis H2b which support this factor as beta is 0.2181 with $p<0.01$, showing highly significant impact.

Competitive pressure plays a significant and positive role in driving adoption of AI Technology, as supported by H3a in this study, where beta is 0.0721 with $p<0.05$, showing significant impact. External competitive pressure influences the adoption of AI technology in recruitment, aligning with the hypothesis of this study. Therefore, firms are compelled to adopt AI to remain competitive, establishing competitive pressure as a crucial factor in AI adoption for recruitment.

In the TOE model's environmental factor, vendor support positively influences AI technology adoption, as confirmed by last hypothesis in this study, as beta is 0.1624 with $p<0.01$ showing highly significant effect. Effective AI technology adoption in recruitment relies on vendor guidance during adoption and implementation (Alam et al., 2016; Ghobakhloo et al., 2011). Continuous support and training are crucial for smooth integration.

The results of this study supported the DOI theory and TOE model. The study is conducted in some selected firms which are involved in recruitment by using AI technology. All the results of this study are accordance with the previous studies of (Bazrkar, Moradzad, & Shayegan, 2024; Daoud, & Kammoun, 2024; Hatoum, & Nassereddine, 2024; Jingjing, & Idris, 2024; Khan, Khan, & Aslam, 2024; Mohammed, Al-Okaily, Qasim, & Al-Majali, 2024; NGUYEN, NGUYEN, & DANG, 2022; Revillod, 2024; Siradhana, & Arora, 2024; Wang, Gao, & Zhang, 2024; Wang, Jiang, Han, Zhou, & Li, 2024; Wang, Li, Zhao, Wang, & Xiao, 2024; Yadav, & Kapoor, 2024)

CONCLUSION

This study primary data is collected through questionnaires by applying TOE model. The analysis was made in smart PLS. The sample of this study was based on those selected firms which were involved in recruitment by using AI technology. All the factors showed a highly significant effect on adoption of AI technology except the one factor; complexity which emerge as weak evidence towards adoption.

The results of this study supported the DOI theory and TOE model. The study is conducted in some selected firms which are involved in recruitment by using AI technology.

The study's findings can help organizations in Pakistan to address challenges in today's environment, particularly in recruitment, by leveraging AI technology. Adopting AI can provide significant advantages, enabling these organizations to gain a competitive edge

The current study is limited to six factors under the TOE model and does not include mediation or moderation analyses.

Future research could address these limitations by incorporating moderators, such as social networks, and mediators, such as adoption, to evaluate their impact on effective HR systems.

REFERENCES

Alam, M. G. R., Masum, A. K. M., Beh, L. S., & Hong, C. S. (2016). Critical factors influencing decision to adopt human resource information system (HRIS) in hospitals. PloS one, 11(8), e0160366.

Bazrkar, A., Moradzad, M., & Shayegan, S. (2024). The Use of Artificial Intelligence in Employee Recruitment in the Furniture Industry of Iran According to the Role of Contextual Factors. *Studia Universitatis „Vasile Goldis" Arad–Economics Series*, *34*(2), 86-109.

Chin, W., & Marcolin, B. (1995). The holistic approach to construct validation in IS research: Examples of the interplay between theory and measurement. Proceedings 23rd Annual Conference of Administrative Sciences Association of Canada, Windsor, Ontario, 3-6 June 1995 (pp. 33–43). UK: Routledge. http://disc-nt.cba.uh.edu/chin/asac95chin&marcolin.pdf

Daoud, Y., & Kammoun, A. (2024). Analyzing and forecasting e-commerce adoption drivers among SMEs: A machine learning approach. *Human Behavior and Emerging Technologies*, *2024*(1), 7747136.

Farhat, R., & Anjum, T. (2024). AI adoption in R&S: exploring different factors of TOE model in Pakistan. Bahria University Journal Of Management & Technology, 7(1).

Fenwick, A., Molnar, G., & Frangos, P. (2024). The critical role of HRM in AI-driven digital transformation: a paradigm shift to enable firms to move from AI implementation to human-centric adoption. Discover Artificial Intelligence, 4(1), 34.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50.

Gefen, D., Straub, D., & Boudreau, M.-C. (2000). Structural equation modeling and regression: Guidelines for research practice. Communications of the Association for Information Systems, 4(1), 7. https://doi.org/10.17705/1CAIS.00407

Hatoum, M. B., & Nassereddine, H. (2024). Determining Decision-Making Factors for Technology Adoption in the Construction Industry.

Hsu, P. F., Kraemer, K. L., & Dunkle, D. (2006). Determinants of e-business use in US companies. International Journal of Electronic Commerce, 10(4), 9–45. https://doi.org/10.2753/ JEC1086-4415100401

Jingjing, Z., & Idris, S. (2024). Determinants of Cross-border E-Commerce Usage Based on TOE Framework of SMEs in Hebei Province. *Malaysian Journal of Social Sciences and Humanities (MJSSH)*, *9*(3), e002692-e002692

Khan, F. A., Khan, N. A., & Aslam, A. (2024). Adoption of Artificial Intelligence in Human Resource Management: An Application of TOE-TAM Model. *Research and Review: Human Resource and Labour Management*, 22-36.

Kline, P. (2013). Handbook of psychological testing. London, UK: Routledge. https://doi.org/10.4324/9781315812274.

Malik, S., Chadhar, M., Vatanasakdakul, S., & Chetty, M. (2021). Factors affecting the organizational adoption of blockchain technology: extending the technology-organization-environment (TOE) framework in the Australian context. *Sustainability*, *13*(16), 9404.

Mohammed, A. B., Al-Okaily, M., Qasim, D., & Al-Majali, M. K. (2024). Towards an understanding of business intelligence and analytics usage: Evidence from the banking industry. *International Journal of Information Management Data Insights*, *4*(1), 100215.

NGUYEN, T. L., NGUYEN, V. P., & DANG, T. V. D. (2022). Critical factors affecting the adoption of artificial intelligence: An empirical study in Vietnam. *The Journal of Asian Finance, Economics and Business*, *9*(5), 225-237.

Pan, Y., Froese, F., Liu, N., Hu, Y., & Ye, M. (2022). The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. *The International Journal of Human Resource Management*, *33*(6), 1125-1147.

Revillod, G. Recruitment Through Ai in Swiss Organizations: The Importance of Organizational, Environmental, and Contextual Factors. *Environmental and Contextual Factors*.

Rogers, E. (2003). The diffusion of innovations (5th ed.). The Free Press.

Rogers, E. M. (1995). *Diffusion of innovations*. New York: Free Press.

Samy, N., Abd El Aziz, R., Tarek, M., & Ismail, M. (2023). HRIS Mediating Role the Relationship between TOE and Decision Making. *Technology and Investment*, *14*(1), 1-21.

Siradhana, N. K., & Arora, R. G. (2024). Examining the Influence of Artificial Intelligence Implementation in HRM Practices Using TOE Model. *Vision*, 09722629241231458.

Sjöberg, R., & Schill, D. (2023). Examining Key Factors for Organizational Readiness towards AI Adoption in the Software Industry: A Qualitative Study.

Syeda, S. H. (2018). An exploratory study to identify critical success factors of agile systems engineering (Doctoral dissertation). The George Washington University.

Tornatzky, L. G., & Fleischer, M. (1990). The processes of technological innovation. Lexington. *MA: Lexington Books*.

Wang, S., Gao, M., & Zhang, H. (2024). Strengthening SMEs competitiveness and performance via industrial internet: Technological, organizational, and environmental pathways. *Humanities and Social Sciences Communications*, *11*(1), 1-15.

Wang, Y., Jiang, H., Han, D., Zhou, M., & Li, G. (2024). How top leaders' support affects open government data (OGD)-driven innovation capacity of firms: Based on the TOE framework perspective. *Journal of Management & Organization*, 1-17.

Wang, Z., Li, Y., Zhao, X., Wang, Y., & Xiao, Z. (2024). Research on predicting the driving forces of digital transformation in Chinese media companies based on machine learning. *Scientific Reports*, *14*(1), 7286.

Yadav, S., & Kapoor, S. (2024). Adopting artificial intelligence (AI) for employee recruitment: the influence of contextual factors. *International Journal of System Assurance Engineering and Management*, *15*(5), 1828-1840.