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Artificial Intelligence in Talent Acquisition, Do we Trust It?

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ABSTRACT

This study aims to investigate HR leaders' trust in AI application in talent acquisition and the role of technology trust as a predictor of HR leaders' attitude toward its adoption. The sample was drawn from the HR professionals' network in the Middle East using an online survey with 389 responses. The study results concluded that HR leaders have a positive attitude toward the adoption of AI applications in the talent acquisition function. Additionally, HR leaders perceived it as highly advantageous and this perception positively influenced their attitude. Further, it is concluded that. HR leaders possess high trust in AI-based talent acquisition solutions and that their perception about its reliability, credibility and technical competence are significant predictors of this trusting belief.

1. INTRODUCTION

Ever Since its emergence, the function of Human Resources Management (HRM) fundamental contribution for organizations and economies have been subject to substantial transformations and development. Among the major factors of which sparked these transformations is Information Technology (IT) innovations development (Troshani, Jerram and Hill, 2011). The diffusion of IT within the HRM function can be traced back as early as the invention of computers and IT systems. However, the level and intensity of this IT contribution to the HRM function were very much connected with the development and advancement in IT. For instance, early Human Resources Information systems (HRIS) have gradually endorsed the computerization of HRM tasks which enabled organizations to digitally process, store, and share HR-related data. Later on, with internet invention, the concept of Electronic-HR (e-HR) have emerged which provided an interactive medium that integrated the stakeholders despite their geographical disengagement and implements HR strategies and tasks virtually crossing the organizational boundaries through web-technologies (Ruël, Bandarouk and Looise, 2004; Strohmeier, 2007). Talent Acquisition (also referred to as recruiting, staffing, and hiring) is the HRM function in which defined as the "actions and activities taken by an organization to identify and attract individuals to the organization who have the capabilities to help the organization realize its strategic objectives" (Arne, Anderson and Voskuijl, 2006). It comprises serval essential tasks which begin at the strategic level such as manpower planning and implementation level such as sourcing, screening, assessing candidates, contracting, and on boarding. ITs have had a major impact on the methods by which organizations acquire their HR talents. For instance, early HRIS has enabled recruiters to electronically store, classify, share and process talent acquisition related data which improved efficiency (e.g. time, cost), accuracy, and quality of the talent acquisition function. Moreover, e-HR has substantially transformed talent acquisition function by providing the organization with internet-based means to brand itself, acquire and connect with targeted HR and the conventional hiring methods have been gradually diminished in favour of "e-recruitments".

While certainly HRIS and e-HR have significantly impacted the talent acquisition process at a strategic and operational level, hence, it is noticeable that Artificial Intelligence (AI) based solutions are

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emerging rapidly posing another major IT intervention to the talent acquisition methods. Nowadays, a growing reliance on AI in the talent acquisition process has become visible where interconnectivity and automation represent the emerging approaches in hiring. This reliance is manifested in the heterogeneous talent acquisition solutions in which employ advanced IT techniques such as machine learning, data mining, artificial neural network (ANN), augmented reality. Etc. The distinctive role of these AI-based talent acquisition solutions from traditional HRIS and e-HR is that it promotes augmented intelligence where humans and AI jointly make decisions. For instance, AI solutions that autonomously process the most time-consuming talent acquisition tasks such as candidate sourcing, screening, and communication. Chatbots, intelligent search engines, smart Applicant Tracking Systems (ATS), Candidate Relationship Management (CRM) are examples of trending AI applications within talent acquisition. Nowadays, there is no doubt that Professional Networking Platforms (PNPs) such as LinkedIn are the leading talent acquisition approach with more than 722 million users. At this moment, “AI powers everything at LinkedIn” for instance machine learning models create links between job profiles and, deep learning capture users’ preferences and generate personalized results. Applicant Tracking Systems (ATS) is another AI tool that is being increasingly used in locating both passive and active jobseekers, it produces instantaneous candidates search based on predefined role specifications. Surveys showed that 90% of big sized companies and 68% of SMEs are applying ATS and it is the largest share of the talent acquisition industry (Mondal, 2020). Moreover, other time-consuming talent acquisition tasks of which AI applications offer to handle are candidates screening, shortlisting, and communication. AI-based Candidate Relationship Management (CRM) software such as Chatbots is also being increasingly used to facilitate the talents selections process. For instance, some of the hiring Chatbots provide thorough solutions for talent acquisition by autonomously screen the candidates' profile, initiate instant communication and feedback services throughout the hiring process, assess candidates by conducting screening interviews, request further actions if needed such as in missing data case, and produce a final shortlist of qualified applicants. Sits argued that some Chatbots automate 75% of the talent acquisition process (Dickson, 2017). Also, AI-based talent acquisition solutions (eg. “Affectiva”, “HireVue”) are applied in evaluating candidates' interviews by analysing facial expression and emotion extract techniques and provide inputs about their level of engagement, personality, motivation, and honesty (Boz and Kose, 2018). Moreover, pre-employment background screening is another talent acquisition task that has been recently handed over to AI. For instance, “FAMA” uses natural language to screen the internet, news, blogs, social media, and professional networks to investigate candidates criminal and violent history, workplace misconducts, drug abuse, as well as positive indicators such as volunteering, and other relevant information (Mahmoud *et al.*, 2019).

No doubt that AI's contribution in autonomously handling talent acquisition time-consuming and costly tasks is considered a distinctive elevation of IT role within HRM in general and specifically the talent acquisition functions. This increased reliance on AI and changes in IT roles are argued to significantly alter the conventional talent acquisition methods, redefine recruiter’ competencies, and impact the competition level of HR acquisition. Consequently, researchers, organizations, and policymakers are urged to dedicate enough efforts to understand this phenomenon and prepare these transformations within IT roles within HRM. While HRIS and e-HR adoption have received observable research interest (Kovach and Cathcart, 1999; Kovach *et al.*, 2002; Ngai and Wat, 2004; Florkowski and Olivas-Luján, 2006; Strohmeier, 2007; Teo, Lim and Fedric, 2007; Voermans and Van Veldhoven, 2007; Al-Dmour, Love and Al-Zu’bi, 2013), there is an observable research gap concerning the of AI in talent acquisition adoption determinants and predictors. Therefore, this study aims to investigate HR leaders’ attitude toward AI application in talent acquisition and the role of the perceived relative advantage and trust as a predictor of HR leaders’ attitude toward its adoption. Moreover, measure the association between the perceived AI applications credibility, reliability and technical competence with trust.

2. STUDY MODEL

To achieve the study objectives A conceptual model has been developed, Figure 1. illustrates the study variables and the hypothesised underlying relationships.

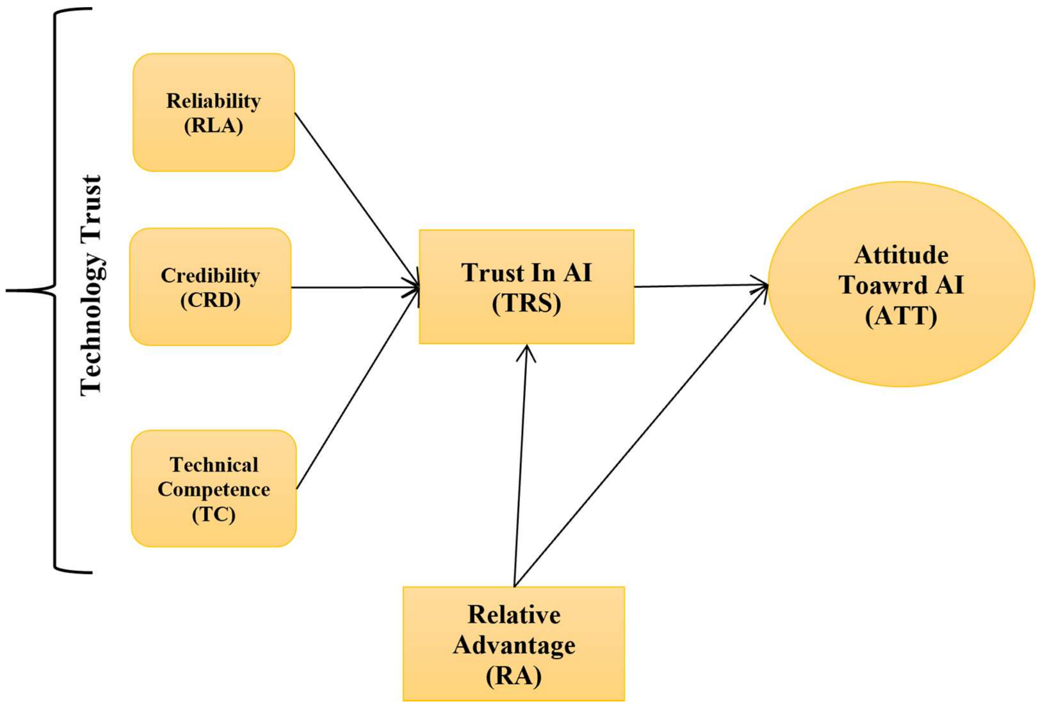

Figure 1. Study Model

2.1. TECHNOLOGY TRUST

Trust is associated with any degree of uncertainty. In General, trust is defined as the "psychological expectation that a trusted party will not behave opportunistically, and the willingness of a party to be vulnerable to the actions of other parties" (Kim, Shin and Lee, 2009). The trust relationship has several elements among which interdependency, willingness, expectations, and risk (Kim, Shin and Lee, 2009). From the IT adoption perspective, it is argued that an Individual's trust is a significant predictor of It innovation acceptance and adoption behaviour (Cody-Allen and Kishore, 2006). Due to the rapid leap of IT roles and advancement, understanding users' trust in technology has become essential for the successful implementation and development of IT innovations (Mcknight and Chervany, 2002; Casey and Wilson-Evered, 2012). Consequently, several IT innovations adoption studies (Lee and Turban, 2001; Gefen, 2002; McKnight, Choudhury and Kacmar, 2002; El-Khatib *et al.*, 2003; Pavlou, 2003; Gefen, Karahanna and Straub, 2003; Cody-Allen and Kishore, 2006; Parasuraman, Sheridan and Wickens, 2008; Kim, Shin and Lee, 2009; Luo *et al.*, 2010; Yusoff, Ramayah and Othman, 2015; El-Masri and Tarhini, 2017) have investigated the influence of trust on the adoption decision.

As an effort to explain the phenomenon of technology trust, heterogeneous research contributions have been produced, thus their effectiveness in achieving this purpose is controversial. However, it is noticeable that some models have consistently appeared in organizational trust research such as (Mayer, Davis and Schoorman, 1995) trustworthiness factors model. Mayer et al., (1995) identify three beliefs of trustworthiness namely: benevolence, competence, and integrity. Benevolence is the belief that trustee intention to act in favour of trustor aside from solely seeking profit, competence is the belief that the trusted party has the capability, skills, and characteristics to deliver the required result, while integrity is "the trustor's perception that the trustee adheres to a set of principles that the trustor finds acceptable" (Mayer, Davis and Schoorman, 1995). However, some other studies (Lippert and Swiercz, 2005; Thatcher *et al.*, 2011) have argued that using organizational interpersonal trust theories (e.g. Mayer et al., (1995) Trustworthiness factors model) in technology trust context is doubtful because of the difference in directionality and predisposition between interpersonal and technological trust relationship. Therefore, alternative dimensions of trust have been introduced to better fit the human-IT trust context. Table.1 summarizes some of these contributions.

Table 1. Technology Trust Models

Study	Model	Context	Dimensions IT Trust
(Lippert and Swiercz, 2005)	Trust in Information Systems Technology (TIST)	HRIS	Predictability, Reliability, Utility
(Lee and Moray, 1992)	Human- Machine Trust	Trust in Automation	Performance, Process, Purpose
(Söllner *et al.*, 2011)	Explanation and Prediction for The Formation of Trust	Trust in IT Artifacts	Performance, Process, Purpose
(Thatcher *et al.*, 2011)	Trust in information Technology	Knowledge Management Systems	Functionality, Predictability, Helpfulness
(Hasan, Krischkowsky and Tscheligi, 2012)	user-centred Trust (UCT) Model	Trust in Software Systems	Functionality, Helpfulness, Reliability
(Choi and Ji, 2015)		Trust in Autonomous Vehicle	System Transparency, Technical Competence, Situation Management

Source:

It is argued that AI talent acquisition applications present major alterations of the conventional hiring methods and it is proclaimed that it promises to improve the efficiency and quality of talent acquisition such as human errors and bias. However, some allegations about AI's ability to become biased (Hurlburt, 2017), urges the necessity to investigate HR Leaders' and users' trust in AI in talent acquisition. Robinson, (2018) qualitative study assessed the attitude of HR practitioners toward AI in hiring by interviewing HR practitioners at different levels (executives, recruiters, HR information systems analysts) at international organizations headquartered in the North-eastern region of the United States. The study addressed the notion of AI application trust and the interviewees have expressed high concerns and conservative attitude. This study utilizes the earlier well-supported conceptualization of IT trust to investigate the determinants of HR leaders' trust in AI in talent acquisition and its influence on their attitude toward adopting these applications (see Figure 1). Three beliefs have been defined as predictors of trust, the first is Technical competence of which reflects HR leaders' perception of AI capability and competence to produce the expected results when autonomously process time-consuming talent acquisition tasks. The second is the HR leaders' belief about AI reliability in terms of delivering consistent and predictable results. Lastly HR leaders' belief about AI credibility reflect its adequacy, compliance with ethical practices such as privacy, and biased concerns.

2.2. Relative Advantage

Relative advantage is defined as "is the degree to which an innovation is perceived to be better than the idea it supersedes" (Rogers, 2003). Studies (Ramamurthy and Premkumar, 1995; Premkumar and Roberts, 1999; Wang, Wang and Yang, 2010) have emphasized Relative advantage as the strongest characteristics of innovation of which predict the IT innovation's acceptance and adoption decision. It means that the higher the perceived gained the relative advantage of an IT innovation, the more likely to adopt it. These advantages are most likely in terms of gained social and benefits, increased comfort and security, facilitating the decision-making process, or generally enhanced efficiency (Rogers, 2003; Lin and Chen, 2012). Previous investigations (Teo, Lim and Fedric, 2007; Parry and Wilson, 2009; Low, Chen and Wu, 2011; Ahmer, 2013; Oliveira, Thomas and Espadanal, 2014; Chaveesuk and Horkondee, 2015; Yang *et al.*, 2015; Martins, Oliveira and Thomas, 2016; Puklavec, Oliveira and Popovič, 2018; Zaied, Grida and Hussein, 2018) have shown relative advantage as a significant predictor of business intelligence, HRIS, and cloud computing, and other IT innovation adoption. This study aims to investigate the influence of relative advantage on HR leaders' trust and attitude toward adopting AI talent acquisition applications. The study hypotheses are presented in Table 2.

Table 2. Study Hypotheses

H1: Reliability influences HR leaders' Trust in AI in talent acquisition.
H2: Credibility positively influences HR leaders' Trust in AI in talent acquisition.
H3: Technical competence positively influences HR leaders' Trust in AI in talent acquisition.
H4: Relative Advantage positively influences HR leaders' Trust in AI in talent acquisition
H5: Relative Advantage positively influences HR leaders' attitude toward the adoption of AI in talent acquisition.
H6: Trust positively influences HR leaders' attitude toward the adoption of AI in talent acquisition.

Source:

3. METHODS

3.1. PARTICIPANTS AND PROCEDURES

To empirically investigate the study hypothesized relationships, the online survey methodology was used. This study targeted population is HR Leaders who are considered as HR policymakers and holds specific predefined senior positions within the organization. The sample was drawn from the HR professionals' network in the Middle East at the LinkedIn professional network platform (PNP). Table 3. illustrates the set of criteria in which were hired to define the target population.

Table 3. Criteria for Defining the Targeted Population

Countries	Jordan, Kuwait, Qatar, Saudi Arabia
Position Title	HR Manager, Senior HR Manager, HR Director, Chief Human Resources Officer (CHRO)
Profile language	English
Other Criteria	Defined employer (unambiguous employment status)

Source:

Using the defined filtering criteria, the size of the sample frame of HR leaders was 8200 which stratified into four stratums based on the country of employment. Referring to Sekaran & Bougie, (2016) scientific guideline for sample size table, a population size of 8000 to 9000 elements requires a minimum sample of 368, hence, Sekaran & Bougie, (2016) argued that for most research, sample sizes of more than 30 respondents and less than 500 is appropriate. The questionnaire was sent online throughout the month of Jul-2020 to one thousand HR Leaders drawn from the defined population stratums using a systematic disproportionate stratified random sampling and a total of 389 valid responses received.

3.2. INSTRUMENT

The instrument was developed based on previous IT innovations adoption studies where the validity and reliability of measurements have been consistently exhibited (see Table. 4), however, measurements were slightly revised to fit the research context.

Table 4. Instrument Measures

Variables	Items	Scale	Sources
Relative Advantage (RA)	5	Likert Scale (1= Strongly disagree; 5= strongly agree)	(Teo, Lim and Fedric, 2007; Martins, Oliveira and Thomas, 2016)
Reliability (RLA)	4		(Thatcher *et al.*, 2011; Choi and Ji, 2015)
Credibility (CRD)	4		
Technical Competence (TC)	4		
Trust (TRS)	3		
Attitude Toward AI adoption (ATT)	6		(Venkatesh *et al.*, 2003; Voermans and Van Veldhoven, 2007)
Total	**26**		

Source: Authors' Construction

4. ANALYSIS AND RESULTS

To analyse the study's qualitative primary data, this study employed the Covariance-Based Structural Equation Modelling (CB-SEM) technique. CB-SEM is a commonly used method for assessing relationships among path models and it facilitates the opportunity to perform path-analytic modelling with multiple constructs (Hair, Gabriel and Patel, 2014). SEM technique has several advantages among which its effectiveness in analysing associations between multiple variables and allows eliminating weak measurement to reduces the level of errors within the model (Hair, Gabriel and Patel, 2014).

4.1. Reliability and Validity

Two phases of statistical analysis are performed. The first to examine the validity and reliability of the measurement scale, a confirmatory factor analysis (CFA) was performed. At first, factor loadings of each observed indicator on their underlying observed constructs were examined to validate the measurements' internal consistency. (Chin, 1998; Hair, Gabriel and Patel, 2014) items loadings above the 0.6 threshold are considered sufficient. Items Loading ranged from the lower value of 0.639 for the RLA1 indicator to the higher loading value of 0.922 for the RLA2. Hence, all indicators' standard loadings have met the rule of thumb value at 0.6 threshold at $p<0.000$ significance which indicates that the factors extract sufficient variance from that measurement variables. Additionally, to validate the instrument reliability and convergent validity, Cronbach's α, Average Variance Extracted (AVE) and Composite Reliability (CR) Coefficient were extracted. Researchers recommend that to confirm scale reliability the rule of thumb value of Cronbach's *a* is above 0.7, while the confirmatory value for CR is higher than 0.8 threshold, and 0.5 for AVE (Bagozzi and Yi, 1988; Hair, Gabriel and Patel, 2014). Illustrated in Table 5. The study variables Cronbach's α have met the rule of thumb value of 0.7 and the overall *α* value for the study instrument is 0.968. further, the AVE and CR values for the study variables have met the confirmatory value of 0.5, 0.8 respectively. Accordingly, based on these outputs the study instrument internal consistency, reliability, and convergent validity have been confirmed.

Table 5. Validity and Reliability Measures

Factor	Item	loadings	Cronbach's Alpha (*α*)	AVE	CR
Attitude Toward AI adoption (ATT)	ATT1	0.648	0.944	0.693	0.930
	ATT2	0.891			
	ATT3	0.889			
	ATT4	0.866			
	ATT5	0.753			
	ATT6	0.915			
Credibility (CRD)	CRD1	0.889	0.846	0.582	0.846
	CRD2	0.693			
	CRD3	0.655			
	CRD4	0.793			
Reliability (RLA)	RLA1	0.639	0.845	0.574	0.841
	RLA2	0.922			
	RLA3	0.762			
	RLA4	0.676			
Technical Competence (TC)	TC1	0.718	0.851	0.599	0.855
	TC2	0.645			
	TC3	0.806			
	TC4	0.903			
Trust (TRS)	TRS1	0.774	0.852	0.535	0.801
	TRS2	0.732			
	TRS3	0.685			
Relative Advantage (RA)	RA1	0.862	0.908	0.666	0.909
	RA2	0.881			
	RA3	0.819			

	RA4	0.729			
	RA5	0.781			
Overall Alpha (α)			0.968		

Source:

4.2. Relationships and Hypothesis Testing

The Second phase of statistical analysis was evaluating the SEM and test the hypnotized relationships between the study constructs using AMOS. 21 SEM. A bootstrap with 500 samples was executed and the hypothesized relationships between the study constructs were tested by measuring the Standardized regression weight (β), standardized error; (SE), critical ratio (CR), and their significance levels (p). As shown in Table 6, The lower standardized path coefficient is at the value of -0.106 for the significant negative relationship between employee Relative Advantage (RA) and Trust (TRS) while the higher coefficient is 0.731 for the significant positive relationship between the Technical Competence (TC) and Trust (TRS). Among the sixth study hypotheses, H1, H2, H3, H5, H6 are supported, while H4 is rejected (see Table 6).

Table 6. Relationships and Hypothesis Testing

Predictors OF Trust (TRS)						
Hypotheses	Construct	Estimate	S.E.	C.R.	P	Result
H1	Reliability (RLA)	0.591	0.058	10.253	***	Supported
H2	Credibility (CRD)	0.159	0.025	6.454	***	Supported
H3	Technical Competence (TC)	0.731	0.058	12.68	***	Supported
H4	Relative Advantage (RA)	-0.106	0.024	-4.443	***	Rejected
Predictors of Attitude Toward AI adoption (ATT)						
H5	Relative Advantage (RA)	0.226	0.041	5.472	***	Supported
H6	Trust (TRS)	0.362	0.058	6.204	***	Supported

Source:

4.3. Discussion

This study aims to investigate the adoption predictors of emerging AI applications in talent acquisition. Specifically, the study has tackled the phenomenon of technology trust in these applications from HR leaders' perspectives. At first, the study investigated the level of significance between Reliability (RLA), Credibility, Technical Competence, and the perceived Relative Advantage and HR leaders' trust in AI applications. Secondly, the association between Relative Advantage and Trust with HR leaders' attitude toward the adoption of AI in talent acquisition. In general, the independent variable (ATT) mean value (3.89, max=5) reveals that HR leaders have a relatively high positive attitude toward AI application in talent acquisition. Also, among the study variables, the higher responses mean value of 4.01 is for the relative advantage variable which reveals that HR leaders perceive AI applications as highly advantageous. Moreover, a mean value of (3.95) for the trust factor indicates that HR leaders possess a high degree of trust toward AI application in talent acquisition. Among the mean values for the trust predictors (reliability, credibility, technological competence), reliability had the higher value of 4.00 which reveals that HR leaders perceive AI as a reliable and predictable tool. The mean value for credibility predictor is 3.97 which also considered an optimistic stance about AI credibility. Lastly, among the trust predictors, technological competence has had the lowest mean value of 3.91, hence, it is considered a positive belief about AI application competence.

Confirming H1, results show that reliability is a significant predictor of trust β=0.591 at p=0.000. this result reveals the extent to which HR leaders perceive AI as predictable and consistent, and their capability to forecast its operating methods for a specific talent acquisition task significantly and positively influence their trust in it. Likewise, results support the credibility significant positive prediction of AI trust at β=0.159 at p=0.000. This result indicates that the higher HR leaders' perception of AI adequacy, accuracy, truthfulness, integrity, and non-biased processing of talent acquisition tasks, the more they trust it and confirming H2. Technological competence measured the HR leaders' belief about AI proficiency and effectiveness in autonomously handling talent acquisition tasks such as applicants sourcing, screening, and shortlisting. Confirming H3, the result revealed that technological competence is the strongest significant positive predictor (β=0.731 at p=0.000) of HR leaders' trust in AI applications in talent acquisition. This result is consistent with previous studies (Gefen, 2002; McKnight, Choudhury and Kacmar, 2002; El-Khatib *et al.*, 2003; Gefen, Karahanna and Straub, 2003; Cody-Allen and Kishore, 2006; Parasuraman, Sheridan and Wickens, 2008; Kim, Shin and Lee, 2009; Yusoff, Ramayah and Othman, 2015; El-Masri and Tarhini, 2017) which have confirmed the Trust as a predictor of IT adoption. A positive influence of relative advantage on HR leaders' trust was hypothesized, thus, contrary to our expectation the results have revealed a negative relationship rejecting H4.

The second objective of this study was to investigate the relative advantage and trust influence on HR leaders' attitude toward the adoption of AI in talent acquisition. Confirming previous studies of IT innovations adoption (Teo, Lim and Fedric, 2007; Parry and Wilson, 2009; Low, Chen and Wu, 2011; Ahmer, 2013; Oliveira, Thomas and Espadanal, 2014; Chaveesuk and Horkondee, 2015; Yang *et al.*, 2015; Martins, Oliveira and Thomas, 2016; Puklavec, Oliveira and Popovič, 2018; Zaied, Grida and Hussein, 2018) and the hypnotized relationship, relative advantage has a significant positive influence (β=0.226 at p=0.000) on HR leaders' attitude toward the adoption of AI. This indicates that when HR leaders perceive AI applications as helpful in terms of improving talent acquisition productivity, efficiency, quality, and competitive power, they would have a positive attitude toward its adoption. Besides, for the trust factor, it has been found that trust is a significant positive predictor (β=0.362 at p=0.000) of attitude toward AI adoption which supports the H6.

5. CONCLUSIONS

This study addressed the phenomenon of HR practitioners' trust in emerging AI applications in talent acquisition. This study empirically contributes to IT innovations adoption research and the HRIS diffusion and adoption theory. It is concluded that HR leaders have a positive attitude toward the adoption of AI applications in the talent acquisition function. Additionally, HR leaders perceived it as highly advantageous and this perception positively influenced their attitude. Further, it is concluded that HR leaders possess high trust in AI-based talent acquisition solutions and that their perception about its reliability, credibility and technical competence are significant predictors of this trusting belief. These conclusions confirm the general tendency of increased reliance on AI and machine learning within business operations. Moreover, the continuance emerging dependence on AI and automation in processing time-consuming talent acquisition tasks support the proposition of augmented intelligence in HRM. This transformation in IT role might compose a competitive threat for organizations that lag behind and may hinder the organization's ability to acquire and retain qualified HR. Therefore, HR leaders and policymakers are urged to remain informed about AI development research, market adoption practices, and the potential influence on HRM.

REFERENCES

Ahmer, Z. (2013) 'Adoption of human resource information systems innovation in Pakistani organizations', *Journal of Quality and Technology Management*, 9(2), pp. 22–50.

Al-Dmour, R. H., Love, S. and Al-Zu'bi, Z. (2013) 'Factors Influencing the Adoption of HRIS Applications : A Literature Review', *International Journal of Management & Business Studies*, 3(4), pp. 9–25.

Arne, E., Anderson, N. and Voskuijl, O. (2006) *The Blackwell Handbook of Personnel Selection*. Blackwell Publishing. doi: 10.1111/j.1744-6570.2006.00052_4.x.

Bagozzi, R. and Yi, Y. (1988) 'On the Evaluation of Structure Equation Models', *Journal of the Academy of Marketing Science*. doi: 10.1007/BF02723327.

Boz, H. and Kose, U. (2018) 'Emotion Extraction from Facial Expressions by Using Artificial Intelligence Techniques', *BRAIN – Broad Research in Artificial Intelligence and Neuroscience*, 9(1), pp. 5–16. Available at: https://www.edusoft.ro/brain/index.php/brain/article/view/744/850.

Casey, T. and Wilson-Evered, E. (2012) 'Predicting uptake of technology innovations in online family dispute resolution services: An application and extension of the UTAUT', *Computers in Human Behavior*. Elsevier Ltd, 28(6), pp. 2034–2045. doi: 10.1016/j.chb.2012.05.022.

Chaveesuk, S. and Horkondee, S. (2015) 'An integrated model of business intelligence adoption in Thailand logistics service firms', *Proceedings - 2015 7th International Conference on Information Technology and Electrical Engineering: Envisioning the Trend of Computer, Information and Engineering, ICITEE 2015*, pp. 604–608. doi: 10.1109/ICITEED.2015.7409018.

Chin, W. W. (1998) 'Issues and opinion on structural equation modeling', *MIS Quarterly: Management Information Systems*.

Choi, J. K. and Ji, Y. G. (2015) 'Investigating the Importance of Trust on Adopting an Autonomous Vehicle', *International Journal of Human-Computer Interaction*. Taylor & Francis, 31(10), pp. 692–702. doi: 10.1080/10447318.2015.1070549.

Cody-Allen, E. and Kishore, R. (2006) 'An extension of the UTAUT model with e-quality, trust, and satisfaction constructs', *SIGMIS CPR'06 - Proceedings of the 2006 ACM SIGMIS CPR Conference*, 2006, pp. 82–89.

El-Khatib, K. *et al.* (2003) 'Privacy and Security in E-Learning', *International Journal of Distance Education Technologies (IJDET)*, 1(4), pp. 1–19. doi: 10.4018/jdet.2003100101.

El-Masri, M. and Tarhini, A. (2017) 'Factors affecting the adoption of e-learning systems in Qatar and USA: Extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)', *Educational Technology Research and Development*. Springer US, 65(3), pp. 1–21. doi: 10.1007/s11423-016-9508-8.

Florkowski, G. W. and Olivas-Luján, M. R. (2006) 'The diffusion of human-resource information-technology innovations in US and non-US firms', *Personnel Review*, 35(6), pp. 684–710. doi: 10.1108/00483480610702737.

Gefen, D. (2002) 'Reflections on the Dimensions of Trust and Trustworthiness among Online Consumers', *Database for Advances in Information Systems*, 3(3), pp. 38–53.

Gefen, D., Karahanna, E. and Straub, D. W. (2003) 'Trust and TAM in Online Shopping: An Integrated Model', *MIS Quarterly: Management Information Systems*, 27(1), pp. 51–90.

Hair, J. F., Gabriel, M. L. D. da S. and Patel, V. K. (2014) 'AMOS Covariance-Based Structural Equation Modeling (CB-SEM): Guidelines on its Application as a Marketing Research Tool', *Revista Brasileira de Marketing*, 13(02), pp. 44–55. doi: 10.5585/remark.v13i2.2718.

Hasan, Z., Krischkowsky, A. and Tscheligi, M. (2012) 'Modelling User-Centered-Trust (UCT) in software systems: Interplay of trust, affect and acceptance model', *Lecture Notes in Computer Science*, pp. 92–109. doi: 10.1007/978-3-642-30921-2_6.

Hurlburt, G. (2017) 'How Much to Trust Artificial Intelligence?', *IEEE Computer Society*, 19(4), pp. 7–11.

Kim, G., Shin, B. and Lee, H. G. (2009) 'Understanding dynamics between initial trust and usage intentions of mobile banking', *Information Systems Journal*, 19(3), pp. 283–311. doi: 10.1111/j.1365-2575.2007.00269.x.

Kovach, K. A. *et al.* (2002) 'Administrative and Strategic Advantages of HRIS', *Employment Relations Today*, 29(2), pp. 43–48. doi: 10.1002/ert.10039.

Kovach, K. A. and Cathcart, C. E. (1999) ‘Human Resource Information Systems (HRIS): Providing Business with Rapid Data Access, Information Exchange and Strategic Advantage’, *Public Personnel Management*, 28(2), pp. 275–281. doi: 10.1177/009102609902800208.

Lee, J. and Moray, N. (1992) ‘Trust, control strategies and allocation of function in human-machine systems’, *Ergonomics*, 35(10), pp. 1243–1270. doi: 10.1080/00140139208967392.

Lee, M. K. O. and Turban, E. (2001) ‘A trust model for consumer internet shopping’, *International Journal of Electronic Commerce*, 6(1), pp. 75–91. doi: 10.1080/10864415.2001.11044227.

Lin, A. and Chen, N. C. (2012) ‘Cloud computing as an innovation: Perception, attitude, and adoption’, *International Journal of Information Management*, 32(6), pp. 533–540. doi: 10.1016/j.ijinfomgt.2012.04.001.

Lippert, S. K. and Swiercz, P. M. (2005) ‘Human resource information systems (HRIS) and technology trust’, *Journal of Information Science*, 31(5), pp. 340–353. doi: 10.1177/0165551505055399.

Low, C., Chen, Y. and Wu, M. (2011) ‘Understanding the determinants of cloud computing adoption’, *Industrial Management and Data Systems*, 111(7), pp. 1006–1023. doi: 10.1108/02635571111161262.

Luo, X. *et al.* (2010) ‘Examining multi-dimensional trust and multi-faceted risk in initial acceptance of emerging technologies: An empirical study of mobile banking services’, *Decision Support Systems*, 49(2), pp. 222–234. doi: 10.1016/j.dss.2010.02.008.

Mahmoud, A. A. *et al.* (2019) ‘Performance Predicting in Hiring Process and Performance Appraisals Using Machine Learning’, *2019 10th International Conference on Information and Communication Systems (ICICS)*. IEEE, pp. 110–115. doi: 10.1109/iacs.2019.8809154.

Martins, R., Oliveira, T. and Thomas, M. A. (2016) ‘An empirical analysis to assess the determinants of SaaS diffusion in firms’, *Computers in Human Behavior*. Elsevier Ltd, 62, pp. 19–33. doi: 10.1016/j.chb.2016.03.049.

Mayer, R. C. ., Davis, J. H. and Schoorman, F. . D. (1995) ‘An Integrative Model of Organizational Trust Author’, *Academy of Management Review*, 20(3), pp. 709–734.

Mcknight, D. H. and Chervany, N. L. (2002) ‘What Trust Means in E-Commerce Customer Relationships : An Interdisciplinary Conceptual Typology Relationships : Typology An Interdisciplinary Conceptual’, *International Journal of Electronic Commerce*, 6(2), pp. 35–59. doi: 10.1080/10864415.2001.11044235.

McKnight, D. H., Choudhury, V. and Kacmar, C. (2002) ‘Developing and validating trust measures for e-commerce: An integrative typology’, *Information Systems Research*, 13(3), pp. 334–359. doi: 10.1287/isre.13.3.334.81.

Mondal, S. (2020) *The 38 Top Recruiting Software Tools Of 2020*, *Ideal.* Available at: https://ideal.com/top-recruiting-software/#:~:text=According to OnGig%2C the most, for recruiting and staffing agencies.

Ngai, E. W. T. and Wat, F. K. T. (2004) ‘Human resource information systems : a review and empirical analysis’, *Personnel Review*, 35(3), pp. 297–314. doi: 10.1108/00483480610656702.

Oliveira, T., Thomas, M. and Espadanal, M. (2014) ‘Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors’, *Information and Management*. Elsevier B.V., 51(5), pp. 497–510. doi: 10.1016/j.im.2014.03.006.

Parasuraman, R., Sheridan, T. B. and Wickens, C. D. (2008) ‘Situation Awareness, Mental Workload, and Trust in Automation: Viable, Empirically Supported Cognitive Engineering Constructs’, *Journal of Cognitive Engineering and Decision Making*, 2(2), pp. 140–160. doi: 10.1518/155534308X284417.

Parry, E. and Wilson, H. (2009) ‘Factors influencing the adoption of online recruitment’, *Personnel Review*, 38(6), pp. 655–673. doi: 10.1108/00483480910992265.

Pavlou, P. A. (2003) ‘Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model’, *International Journal of Electronic Commerce*, 7(3), pp. 101–134. doi: 10.1080/10864415.2003.11044275.

Premkumar, G. and Roberts, M. (1999) ‘Adoption of new information technologies in rural small businesses’, *Omega*, 27(4), pp. 467–484. doi: 10.1016/S0305-0483(98)00071-1.

Puklavec, B., Oliveira, T. and Popovič, A. (2018) ‘Understanding the determinants of business intelligence system adoption stages an empirical study of SMEs’, *Industrial Management and Data Systems*, 118(1), pp. 236–261. doi: 10.1108/IMDS-05-2017-0170.

Ramamurthy, K. and Premkumar, G. (1995) ‘Determinants and Outcomes of Electronic Data Interchange

Diffusion', *IEEE Transactions on Engineering Management*, 42(4), pp. 332–351. doi: 10.1109/17.482083.

Robinson, M. F. (2019) *AI in Hiring: Understanding attidues and perspectives of HR practitioners*. ProQuest Dissertations Publishing. doi: 13424889.

Rogers, E. M. (2003) *Diffusion of Innovations*. Fifth Edit. New York: The Free Press.

Ruël, H., Bandarouk, T. and Looise, J. K. (2004) 'E-HRM: Innovation or Irritation. An Explorative Empirical Study in Five Large Companies on Web-based HRM', *Management Revue*, 15(3), pp. 364–380.

Sekaran, U. and Bougie, R. (2016) *Research Methods for Business*. Seventh ed. Chichester: John Wiley & Sons Ltd. doi: 10.1007/978-94-007-0753-5_102084.

Söllner, M. *et al.* (2011) 'Towards a Theory of Explanation and Prediction for the Formation of Trust in IT Artifacts', *SIGHCI 2011 Proceedings. Paper 6*, (2011), p. 6. Available at: http://aisel.aisnet.org/sighci2011/6.

Strohmeier, S. (2007) 'Research in e-HRM: Review and implications', *Human Resource Management Review*, 17(1), pp. 19–37. doi: 10.1016/j.hrmr.2006.11.002.

Teo, T., Lim, G. S. and Fedric, S. A. (2007) 'The adoption and diffusion of human resources information systems in Singapore', *Asia Pacific Journal of Human Resources*, 45(1), pp. 44–62. doi: 10.1177/1038411107075402.Teo.qxd.

Thatcher, J. B. *et al.* (2011) 'The role of trust in postadoption IT exploration: An empirical examination of knowledge management systems', *IEEE Transactions on Engineering Management*, 58(1), pp. 56–70. doi: 10.1109/TEM.2009.2028320.

Troshani, I., Jerram, C. and Hill, S. R. (2011) 'Exploring the public sector adoption of HRIS', *Industrial Management and Data Systems*, 111(3), pp. 470–488. doi: 10.1108/02635571111118314.

Venkatesh, V. *et al.* (2003) 'USER ACCEPTANCE OF INFORMATION TECHNOLOGY: TOWARD A UNIFIED VIEW', 27(3), pp. 425–478.

Voermans, M. and Van Veldhoven, M. (2007) 'Attitude towards E-HRM: An empirical study at Philips', *Personnel Review*, 36(6), pp. 887–902. doi: 10.1108/00483480710822418.

Wang, Y. M., Wang, Y. S. and Yang, Y. F. (2010) 'Understanding the determinants of RFID adoption in the manufacturing industry', *Technological Forecasting and Social Change*. Elsevier Inc., 77(5), pp. 803–815. doi: 10.1016/j.techfore.2010.03.006.

Yang, Z. *et al.* (2015) 'Understanding SaaS adoption from the perspective of organizational users: A tripod readiness model', *Computers in Human Behavior*. Elsevier Ltd, 45, pp. 254–264. doi: 10.1016/j.chb.2014.12.022.

Yusoff, Y. M., Ramayah, T. and Othman, N.-Z. (2015) 'Why Examining Adoption Factors, HR Role and Attitude towards Using E-HRM is the Start-Off in Determining the Successfulness of Green HRM?', *Journal of Advanced Management Science*, (December 2015), pp. 337–343. doi: 10.12720/joams.3.4.337-343.

Zaied, A. N. H., Grida, M. O. and Hussein, G. S. (2018) 'Evaluation of critical success factors for business intelligence systems using fuzzy AHP', *Journal of Theoretical and Applied Information Technology*, 96(19), pp. 6406–6422.