THE ADOPTION OF ARTIFICIAL INTELLIGENCE IN HUMAN RESOURCE MANAGEMENT

BILAL HMOUD

DOI: 10.23762/FSO_VOL9_NO1_7

ABSTRACT

Artificial Intelligence (AI), machine learning, and automation are rapidly advancing, significantly elevating the role of IT within business processes. From an HRM perspective, emerging AI-based solutions are increasingly relied upon in terms of processing time-consuming and complex tasks within the HRM functionalities. This study tackles the phenomenon of AI-based applications in HRM diffusion and adoption: specifically, the association between the HR roles emphasised within the organisation and the attitude of HR practitioners toward AI adoption, as well as the significance of performance expectancy, top management support, and competitive pressures as predictors of AI adoption in HRM. The study sample consisted of 186 senior HR professionals drawn from members of the Jordanian Human Resources Management Association. Results revealed that top management support and performance expectancy are significant predictors of the intention to adopt AI, while competitive pressure did not turn out to have a significant association with such an intention. For the HR roles emphasised, a significant positive influence on the intention to adopt AI has been found for the HR role of "change agent", while the "employee champion" role possesses a significant negative influence in terms of AI adoption. Considering the noticeable research gap in AI diffusion and adoption within HRM, the study findings provide an important contribution to investigating and explaining this phenomenon. It reveals that HR leaders have a positive mindset toward the potential role of AI in enhancing HRM efficiency and quality.

KEY WORDS

Artificial Intelligence, Human Resource Information Systems, Information Technology Adoption.

BILAL HMOUD
e-mail: bilal.ibrahim.t@gmail.com
University of Debrecen,
Debrecen, Hungary

Introduction

The phenomenon of IT adoption has kept researchers busy so far, and its diffusion and impact on the Human Resource Management (HRM) function has been one of the major HRM research areas. IT innovations are among the key factors which played a major role in the transformation of HRM. Early Human Resource Information Systems (HRIS) and Electronic-HR (e-HR) have enabled organisations to digitally process, store, and disseminate HR-related information among the internal and external stakeholders of an organisation. However, the rapidly growing reliance on Artificial Intelligence (AI)-based solutions, interconnectivity, and automation in processing HR tasks such as talent acquisition has become visible, and is swiftly developing. While AI in HRM poses major changes to conventional HRM methods and despite the considerable amount of literature related to integrating AI with HRIS,

Paper received: 7 December 2020 • Paper revised: 18 February 2021 • Paper accepted: 28 February 2021

research connected to determinants pertaining to its adoption is scarce and lags behind other fields.

Early theoretical research widely explored the potential application of AI within the HR functionalities, including recruitment (Boz and Kose, 2018; Chang, 2010; Chen and Chien, 2011; Daramola et al., 2010; Huang et al., 2004; Kabak et al., 2012; Lin, 2010; Mehrabad and Brojeny, 2007; Sivaram and Ramar, 2010; Tai and Hsu, 2006; Tung et al., 2005), Human Resources Development (HRD) and turnover prediction (Buzko et al., 2016; Sivathanu and Pillai, 2018; Strohmeier and Franca, 2015), Performance Management (PM) (Jing, 2009; Lee, 2010; Rashid and Jabar, 2016; Wu, 2009; Zhao, 2008) and others. While some of these early suggested tools were realised, it did not offer a comprehensive integrated system similar to ERPs, but rather an upgrade which can be integrated with existing HRI systems to improve its capabilities with AI-based algorithms. However, recent advancements in Big Data, connectivity, machine learning, and AI techniques have facilitated the development and diffusion of AI-based HRM applications, which are gaining increased prominence over traditional HRIS. Although HRIS and e-HR made a significant strategic contribution to the development of HRM, for instance in terms of communication, knowledge management and efficiency (Premkumar and Roberts, 1999), they mostly targeted tactical HR applications. What distinguishes AI is that it is designed to promote augmented intelligence where time-consuming tasks are autonomously processed by AI, and humans and software jointly make decisions. This represents a revolutionary uplift of the role of IT which will significantly affect HRM conduct as well as core HR competencies. Intelligent search engines, chatbots, smart Applicant Tracking Systems (ATS), Candidate Relationship Management (CRM), data integration, analytical systems, and virtual reality-based learning systems are among the most used AI-based HR solutions. The potential benefit to the organisation is not limited to cost and timesaving, as it promises a colossal contribution to HRM quality as well. For instance, eliminating human errors and bias, improved customer satisfaction and engagement, and increased competitiveness are among the key HR challenges that AI has the potential to improve.

Part of a broader exploration of AI diffusion in significant HRM determinants, this study is an attempt to fill the research gap within the determinants of AI adoption in HRM research. The emphasis is on selected factors of which have repeatedly appeared in the literature as a significant determinant of IT adoption. Specifically, this study aims to examine the relationships between competitive pressure, top management support, performance expectancy, and the HR roles emphasised within the organisation and HR practitioners' attitude toward the adoption of AI in HRM. Moreover, the objective of this study is to provide valuable input and a better understanding of AI-based HR solutions development and adoption for managers, organisations, and policymakers. Accordingly, a conceptual framework was developed, grounded on the Unified Theory of Acceptance and Use of Technology (UTAUT) and Urlich's model of HR roles.

1. Study model and hypotheses

To attain the study objective, a conceptual framework was constructed (Figure 1) which illustrates the study constructs and their hypothesised relationships. The framework is based on the UTAUT model (Venkatesh et al., 2003) and Ulrich's framework of HR roles (1998).

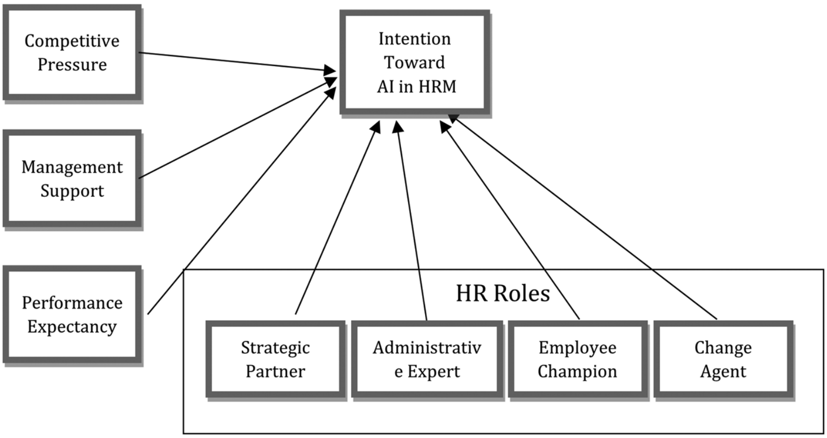
1.1. Independent variables

1.1.1. Competitive pressure

Competitive pressure refers to the amount of pressure perceived by the organisation from its competitors (Oliveira and Martins, 2010). As the world is moving towards a knowledge-based and free-market economy, surveys and economic research indicate that competitive pressure is on the rise. Owing to this pressure, organisations may experience an urge to seek increased competitiveness through the adoption of new IT innovations. Premkumar and Ramamurthy (1995) argued that adopting emerging IT innovations might become a strategic necessity due to intense competition (Ramdani et al., 2009). Empirical evidence argues that intense competition and competitive pressure is an important determinant and strong driver of the adoption of IT innovations (Low et al., 2011). For instance, a study by Low et al. (2011) showed that competitive pressure and trading partner pressure are significant predictors of cloud computing adoption. Similar results were found pertaining to e-business adoption (Oliveira and Martins, 2010), e-supply chain systems (Lin, 2013), and business intelligence (Bhatiasevi and Naglis, 2018). Even though AI in HRM is comparatively at the early diffusion stage, AI applications have become accessible to SMEs with minimal technological computability concern, making it cost-effective. Therefore, this study hypothesised:

H1. Competitive pressure is positively associated with the behavioural intention to adopt AI in HRM.

Figure 1. Research model



Source: Own elaboration.

1.1.2. Management support

Researchers such as Lin and Chen (2012) and Teo (2012) have acknowledged management support as a crucial factor for the adoption and implementation of new IT innovation. Organisations with top management that fosters an innovation-friendly climate, communicates support for it, and provides adequate resources will be more likely to adopt new IT innovations or engage in adoption behaviour when compared with its competitors (Wang et al., 2010). Top management support for technological adoption can be interpreted in a well-communicated organisational vision (Ramdani et al., 2009). Thus, management support might also be highly influenced by the complexity of innovation and competitive pressure. Previous studies have shown that top management support and encouragement for innovation is significant when it comes to creating a highly adoptive atmosphere. For instance, Low et al. (2011) revealed that top management support is a significant predictor of cloud computing adoption. Ramdani et al. (2009), in their study on business intelligence adoption, emphasised that – among other adoption determinants – the support of top management is the most significant determinant of the adoption of IT innovations.

Since AI adoption entails key changes to the existing conventional role of IT within HRM, it is assumed that the strategic direction of top management, their perceptions and familiarities with emerging AI HRM solutions, and their attitude toward investing in IT innovations is a significant predictor of AI adoption in HRM. Thus, the following is hypothesised:

H2. Top management support is positively associated with the behavioural intention to adopt AI in HRM.

1.1.3. Performance expectancy

Performance expectancy is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003). In other words, performance expectancy is the degree to which the potential adopter perceives that utilising a specific IT innovation is beneficial when performing a certain function. Venkatesh, Thong, and Xu (2012) emphasised that performance expectancy is the strongest predictor of adoption intention. Therefore, in this study context, performance expectancy is defined as the degree to which HR professionals perceive that using AI in HRM is functional and their perception of the benefits associated with adopting it. This study hypothesised the following:

H3. Performance expectancy is positively associated with the behavioural intention to adopt AI in HRM.

1.1.4. HR roles

Ulrich, a pioneer researcher in human resources roles and functionalities, argued that information technology would change business processes in general, and specifically HRM practices (Ulrich, 1997), posing the following questions: "will technology connect employees without face-to-face contact? How will technology change communication patterns? How will technology change specific HR practices?" 20 years after addressing these questions, the impact of IT innovations has kept researchers busy preparing to support reinventing work-design and organisations (Hempel, 2004). From the HRM perspective, changes in HR roles within the organisation and the diffusion of IT innovations in HRM are interrelated (Voermans and Van Veldhoven, 2007). This study incorporated HR professionals' perceptions of the HR roles emphasised within the organisation to analyse its association with their attitude toward the adoption of AI in HRM. The Ulrich (1997) HR roles model, which is widely acknowledged by HR practitioners and researchers in both research and practice (Voermans and Van Veldhoven, 2007), is applied. Ulrich's model defines four HR roles. The first is a "Strategic Partner", which highlights the role of HRM in formulating the HR strategies, aligning HR practices with organisational goals and articulating overall organisation strategy (Ulrich, 1998). The second is an "Administrative Expert" which exemplifies the role of HRM in transactional processes and the administrative tasks of organisation personnel (Voermans and Van Veldhoven, 2007). The third is an "Employee Champion", a role which emphasises HRM involvement in maintaining employee engagement and commitment, educating managers in how to achieve high levels of employee morale, and bridging the gap between employees and management. Lastly, the fourth role is that of a "Change Agent". In this role, HRM promotes change management by fostering an adaptive culture that copes with environmental changes such as technology and innovation, enhances organisational capacity for change, and provides daily operational support for employees and managers such as problem-solving. Throughout its diffusion, IT has had a substantial role in reengineering and downsizing administrative roles, "reducing the tension between the strategic and administrative role" (Ellig, 1997). Thus, AI in HRM advances this transformation of roles by increasingly taking over HR administrative tasks.

Several empirical studies (Panayotopoulou et al., 2007; Voermans and Van Veldhoven, 2007) have examined the link between HR roles within the organisation and HR professional attitudes toward IT adoption (e.g. E-HR). For instance, Voermans and Van Veldhoven (2007) found that emphasis on the HR roles of strategic partner and employee champion had a significant positive association with attitudes towards the adoption of e-HRM. Gardner et al. (2003) showed that functional orientation, specifically the HR roles of strategic partner and change agent, had a positive relationship with the attitudes of HR managers and executives towards e-HRM. However, no studies have been found which examine the association between HR roles and the adoption of AI in HRM. This study hypothesised the following:

H4. The strategic partner HRM role is positively associated with the behavioural intention to adopt AI in HRM.

H5. The change agent HRM role is positively associated with the behavioural intention to adopt AI in HRM.

H6. The administrative expert HRM role is positively associated with the behavioural intention to adopt AI in HRM.

H7. The employee champion HRM role is negatively associated with the behavioural intention to adopt AI in HRM.

1.2. Dependent variable

1.2.1. Behavioural intention

Behavioural intention is defined as "the degree to which a person has formulated conscious plans to perform or not perform some specified future behaviour" (Warshaw and Davis, 1985). The adoption intention has regularly been applied to predict the adoption and use of IT (Venkatesh et al., 2003). It is argued that behavioural intention is the most powerful predictor of actual adoption behaviour. Customarily, the intention is incorporated as a variable when the examined IT innovation is at an early diffusion phase. It is noticeable that scholars used actual adoption behaviour when researching widely adopted IT solutions. In the context of the study and as a dependent variable, behavioural intention is used to capture the attitude of HR professionals and intention to adopt AI in HRM, as well as its association with the predicting variables in the study.

2. Materials and methods

2.1. Participants and procedures

A survey methodology was used to empirically investigate the hypothesised relationships. The sampling framework consisted of senior HR professionals who are members of the Jordanian Human Resources Management Association. Since this study investigates the notion of AI adoption within HRM practices, the targeted participants are HR professionals who have decision-making authority that influences the decisions of their organisation pertaining to adoption. Therefore, senior HR practitioners in senior positions (e.g. HR manager, head of HR, CHRO, etc.) have been considered. A convenient sample of 192 members was selected to take part in this study. An e-mail including a link to the online survey was sent to the participants along with a cover letter explaining the purpose of the study. After validating response completion and missing data, 186 responses were retained for final data analysis, excluding six responses due to errors or missing data. The survey was managed in the English language, responses were anonymous, and confidentiality was ensured.

2.2. Instrument

The instrument measures are based on previous IT innovation adoption studies obtained from (Table I) where their validity and reliability have been consistently exhibited. Hence, the items were slightly revised and reworded to fit the study context. Adoption factors are Top Management Support (TMS), Competitive Pressure (CP), Performance Expectancy (PE), and Behavioural Intention (BI). Measurement items for the HR roles, Strategic Partner (SP), Administrative Expert (AE), Employee Champion (EC), and Change Agent (CA), were obtained from Ulrich (1998); yet the measures were reduced and only 20 items were adopted.

Table 1. Study Measurement Items

Constructs	Variables	Items	Measure	Sources
Adoption Factors	Top Management Support (TMS)	3	Likert Scale	(Chong and Chan, 2012; Y.S. Wang et al., 2016)
	Competitive Pressure (CP)	3	Likert Scale	(Y. S. Wang et al., 2016)
	Behavioural intention (BI)	3	Likert Scale	(Venkatesh et al., 2003)
	Performance Expectancy (PE)		Likert Scale	(Venkatesh et al., 2003)
HR Roles	Strategic Partner (SP)	5	Likert Scale	(Ulrich, 1998)
	Employee Champion (EC)	5	Likert Scale	
	Administrative Expert (AE)	5	Likert Scale	
	Change Agent (CA)	5	Likert Scale	

Source: Own elaboration.

3. Research results

The proposed framework was empirically tested using the Covariance-Based Structural Equation Modelling (CB-SEM) technique. SEM is a commonly applied technique for evaluating relationships among path models due to its proven effectiveness in multiple constructs path-analytic modelling (Hair et al., 2014). The SEM approach has several advantages, among which are its effectiveness in examining relationships between multiple constructs while allowing the elimination of weak measurements to reduce the level of errors within the model (Hair et al., 2014). Two levels of statistical analysis were performed. Firstly, to examine the validity and reliability of the measurement scale, a confirmatory factor analysis (CFA) was conducted. The second level was the evaluation of SEM and testing the hypothesised relationships between the study constructs.

3.1. Measurement of reliability and validity

A confirmatory factor analysis (CFA) was performed to examine the validity and reliability of the measurement scale. At first, to validate the internal consistency of the measurements, factor loadings of each observed indicator on their underlying observed construct were examined. Factor loadings above 0.7 are considered ideal (Straub, 1989); however, a value of loadings above 0.5 is considered acceptable (Chin, 1998). The results revealed that the standard factor loadings are higher than 0.7 except for two indicators, CA1 which had a marginal loading of 0.7 (0.685), and CP3 with the lowest loading value of 0.51, yet both items were retained due to meeting the acceptable threshold of 0.5. All loadings were significant at the $p < 0.001$ level, which implies that the factors extract sufficient variance from measurement variables. Furthermore, the instrument reliability and convergent validity were evaluated by extracting the values of Cronbach's α, Average Variance Extracted (AVE), and Composite Reliability (CR) Coefficient for the study constructs. The researchers postulate that, to confirm the reliability of the scale, the rule of thumb for the value of Cronbach's *a* is equal to or higher than 0.7, CR at a threshold of 0.8, and the adequate value of AVE is above 0.5 (Bagozzi and Yi, 1988; Chin, 1998). Without exception, the results show (Table 2) that the Cronbach's α and CR of study constructs have met the rule of thumb value of 0.7 and 0.8, respectively. Moreover, the AVE values have met the 0.50 threshold; therefore, based on these results, the internal consistency, reliability, and convergent validity are confirmed.

To evaluate discriminant validity, the square root of the AVEs of each construct was compared to its correlation with other constructs (Fornell and Larcker, 1981). The results show (see Table 3) that a strong correlation has been found between HR role constructs, ranging from 0.791 between CA and EC to 0.677 between SP and CA, albeit not exceeding the square root value of AVE. All correlations are lower than the square root of the AVEs, meeting Fornell and Larcker's validity test and confirming discriminant validity.

Table 2. Reliability and Validity Measures

Constructs	Indicators	loadings	Estimates		
			Cronbach's a	(AVE)	(CR)
Competitive Pressure (CP)	CP1	0.960			
	CP2	0.850			
	CP3	**0.512**	0.716	0.635	0.914
Top Management Support (TMS)	TMS1	0.842			
	TMS2	0.829			
	TMS3	0.922	0.898	0.749	0.899
Administrative Expert (AE)	AE1	0.792			
	AE2	0.787			
	AE3	0.910			
	AE4	0.911			
	AE5	0.906	0.934	0.745	0.936
Performance Expectancy (PE)	PE1	0.781			
	PE2	0.818			
	PE3	0.796			
	PE4	0.742			
	PE5	0.798	0.890	0.620	0.891
Change Agent (CA)	CA1	**0.685**			
	CA2	0.789			
	CA3	0.875			
	CA4	0.928			
	CA5	0.862	0.911	0.692	0.918

Strategic Partner (SP)	SP1	0.742			
	SP2	0.870			
	SP3	0.926			
	SP4	0.898			
	SP5	0.823	0.927	0.730	0.931
Employee Champion (EC)	EC1	0.672			
	EC2	0.710			
	EC3	0.924			
	EC4	0.940			
	EC5	0.853	0.915	0.684	0.914
Behavioural Intention (BI)	BI1	0.852			
	BI2	0.969			
	BI3	0.903	0.926	0.827	0.935

Source: Own elaboration.

Table 3. Discriminant Validity

Constructs	(MS)	(CP)	(PE)	(SP)	(AE)	(CA)	(EC)
TOP MANAGEMENT SUPPORT (TMS)	**0.865**						
COMPETITIVE PRESSURE (CP)	.388**	**0.797**					
PERFORMANCE EXPECTANCY (PE)	.229**	.278**	**0.787**				
STRATEGIC PARTNER (SP)	0.094	.111*	0.081	**0.854**			
ADMINISTRATIVE EXPERT (AE)	0.041	0.015	0.091	.729**	**0.863**		
CHANGE AGENT (CA)	0.037	0.001	0.071	.677**	.708**	**0.832**	
EMPLOYEE CHAMPION (EC)	0.093	0.049	.116*	.763**	.707**	.791**	**0.827**
BEHAVIOURAL INTENTION (BI)	.187**	.259**	.525**	-0.022	-0.016	-0.041	-0.026

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Source: Own elaboration.

3.2. Structural model and hypotheses testing

The proposed study model was tested using AMOS 21. A bootstrap with 500 samples was executed and the hypothesised relationships between the study constructs were evaluated by extracting the values of standardised regression weight (β), standardised error (SE), critical ratio (CR), and their significance levels (p). As shown in Table 4, the β values have ranged from -0.211 for the significant negative relationship between employee EC and BI, while the higher coefficient is 0.753 for the significant positive relationship between PE and BI toward adopting AI in HRM. Amongst the seven study hypotheses, H1, H3, H4, and H5 are accepted, and H2, H6, and H7 are rejected. The result indicates that TMS – despite the observable positive association with BI – is not significant at the $p=0.05$ level. CP is significantly and positively associated with BI at the $p=0.05$ level. Likewise, from the perspective of HR roles, CA had a significant positive association ($\beta=0.136$, $p=0.000$) with BI, while EC had a significant negative association ($\beta=0.$-211, $p=0.000$) with BI, supporting both hypotheses. However, contrary to the hypotheses, the SP and AE HR roles did not have a significant association with BI.

Table 4. Estimates and Hypotheses Testing

Hypotheses	Construct	Estimate	S.E.	C.R.	P	Result
H1	COMPETITIVE PRESSURE (CP)	0.095	0.047	2.02	0.043*	Supported
H2	TOP MANAGEMENT SUPPORT (TMS)	0.102	0.06	1.687	0.092	Rejected
H3	PERFORMANCE EXPECTANCY (PE)	0.753	0.085	8.806	***	Supported
H4	EMPLOYEE CHAMPION (EC)	-0.211	0.044	-4.771	***	Supported
H5	CHANGE AGENT (CA)	0.136	0.041	3.316	***	Supported
H6	ADMINISTRATIVE EXPERT (AE)	0.003	0.033	0.093	0.926	Rejected
H7	STRATEGIC PARTNER (SP)	0.009	0.034	0.267	0.789	Rejected

*p<0.05, ***p <0.001. Dependent Variable: BEHAVIOURAL INTENTION (BI)

Source: Own elaboration.

4. Discussion

The findings of the statistical analysis offer empirical evidence and substantial insights into the determinants of AI adoption in HRM – specifically, competitive pressure, top management support, and the HR roles within the organisation, as predictors of HR practitioners' intention to adopt AI. The mean values of PE and BI (4.26 and 4.23 respectively) indicate that respondents have a positive perception of the benefits of AI applications as well as a positive adoption intention. Among the study constructs, the strongest predictor of HR practitioners' intention to adopt AI is PE. This result confirms the argument laid out by Venkatesh et al. (2012) that PE has consistently proven to be the strongest predictor of BI. Furthermore, this result confirms Obeidat's (2016) findings that PE has a significant influence on attitudes to adopting e-HR and BI mediation between PE and the actual e-HRM adoption decision. These findings reveal that the perception of the surveyed HR professionals about the benefits and usefulness of AI in HRM highly influence their intention to adopt it when available.

Contrary to the hypothesised relationship, CP had no significant positive association with BI to adopt AI in HRM. Thus, the results contradict those of Chiu et al. (2017), Lin (2013), Low et al. (2011), and Oliveira and Martins (2010), where CP was found to be a significant predictor of the adoption of IT innovation. However, several other studies (Oliveira et al., 2014; Ramdani et al., 2009; Strohmeier and Piazza, 2013; Wang et al., 2016) have also found no empirical evidence that CP is a significant predictor of the adoption of IT innovation. One explanation is that the relationship between competitive pressure and adoption is affected by firm size. Premkumar and Roberts (1999) argued that the smaller the firm, the less significant the influence of CP on the adoption decision. J. Lee (2004) emphasises that small businesses have a different perspective on technology adoption than its contribution to their competitive advantage. The fact this study did not consider firm size as a mediating factor might explain the results. Another possible explanation is that, while AI in HRM is still at the early diffusion stage, some researchers have argued that the significance of competitive pressure is relatively connected with innovation or the prevalence of IT in the late maturity stage rather than the early diffusion stage.

Confirming the findings of several scholars (e.g. Lin, 2013; Martins et al., 2016; Oliveira et al., 2014; Puklavec et al., 2018;

Sun et al., 2018; Yang et al., 2015), this study provides additional evidence of the significant influence of TMS on adoption intention. It reveals that HR practitioners' perception of top management attitude toward IT innovation, their awareness of the benefits thereof, and the likelihood of investing in AI applications are significant predictors of HR practitioners' BI toward the adoption of AI. Mostly, this support is driven by the positive belief and trust of top management in the contribution of IT innovations to improving organisational performance. Furthermore, a vast percentage of organisational adoption research shows that managers of organisations with higher adaptability have a positive attitude toward the contribution made by IT advancements; hence, exploring the possible utilisation of IT innovation manifests in such a strategic direction.

While it is argued that HRIS and e-HR have played a major role in the development of HR roles within organisations, this study aimed to examine HR roles as a predictor of AI adoption in HRM. It is important to note that this study measured the actual HR roles emphasised within the organisation, rather than the preferences pertaining to HR roles. HR personnel have different preferences in terms of HR roles, which reflects their unique beliefs and understanding about the extent of the importance of each role or the expertise required therein. As such, this study measures the actual composition of HR roles. Ulrich (1998) emphasises that the degree of HR professional fulfilment for the four roles varies based on the process design, structure, and other organisational factors. This study hypothesised that the greater the number of strategic partner, change agent and administrative expert roles in the HR department within the organisation, the more positive the attitudes toward AI adoption. On the other hand, however, a negative association was hypothesised for the role of employee champion. The results of the study confirmed that the role of change agent has a positive association with HR practitioners' behavioural intention towards the adoption of AI in HRM. In contrast, the employee champion role is negatively associated with HR practitioners' behavioural intention towards the adoption of AI in HRM, confirming the proposed hypothesis. This result is consistent with a study by Voermans and Van Veldhoven (2007) which examined the relationship between the preferred HR roles and the attitude towards E-HRM systems. On the other hand, no relationships have been found between the administrative expert and strategic partner HR roles and the intention to adopt AI, leading to the rejection of the proposed hypotheses and contradicting Voermans and Van Veldhoven's (2007) results. The absence of any association between strategic HR roles and adoption intention is an interesting outcome which requires further investigation.

While the majority of HRIS research has showed that HR leaders trusted the potential contribution of technology, perceived it as strategically beneficial, and considered its adoption within the strategic planning process, this study shows that generalising and reflecting this premise upon AI adoption is questionable. A possible explanation for this phenomenon is that, while the impact of HRIS and e-HR on HRM and organisational performance were clearly observable, which allowed decision-makers to firmly trust its competitive power, trust in AI-based technology is still debatable. Another possible explanation is the fact that AI-based HR solutions are still in the early diffusion phase and competitive pressure is somehow immature, which might lessen the pressure to strategically consider its adoption. This is also consistent with the absence of any association between competitive pressure and the respondent's adoption intention. Moreover, the significant negative association between the employee champion role and the intention to adopt AI in HRM confirms the speculation that HR leaders who emphasise people over operations perceive HRIS in general as a threat to their role. Although IT has improved organisational communication, it poses a threat to employee champions who crave direct communication and sponsor employees. In fact, the potential contribution of AI to increasing this gap of direct involvement is quite high through taking over a vast percentage of these direct communication tasks. Hence, it poses a question about the future of employee champions among other HR roles. On the other hand, HR leaders who emphasise their role as change agents through greater involvement in organisational transformation and change perceived AI in HRM as an opportunity; therefore, they exhibit a positive intention toward adopting it.

Conclusions

The findings of this study contribute to IT diffusion in HRM theory. The conclusion was drawn that HR leaders have a positive mindset towards the potential role of AI in enhancing HRM efficiency and quality. This conclusion is supported by the fact that respondents did not feel pressure from the competition; hence, they expressed a positive attitude toward adopting AI in HRM, which manifested in their intention to use it if available. The study endorses the claims that the HR change agent role is linked with flexible and adaptive strategies that consider the deviation of the role of IT from current practices, as well as the opposition of the employee champion HR role to the disruptions imposed by IT innovations. While it is believed that AI-based technologies will continue to emerge, offering advanced services and reshaping industries, HR leaders and policymakers are encouraged to remain up-to-date and well-informed about the impact of AI on HRM and organisational effectiveness.

References

Bagozzi, R., Yi, Y. (1988), On the evaluation of structure equation models, Journal of the Academy of Marketing Science, 16, 74-94. https://doi.org/10.1007/BF02723327

Bhatiasevi, V., Naglis, M. (2018), Elucidating the determinants of business intelligence adoption and organizational performance, Information Development, 23(1), 78-96. https://doi.org/10.1177/0266666918811394

Boz, H., Kose, U. (2018), Emotion extraction from facial expressions by using Artificial Intelligence techniques, BRAIN – Broad Research in Artificial Intelligence and Neuroscience, 9(1), 5-16.

Buzko, I., Dyachenko, Y., Petrova, M., Nenkov, N., Tuleninova, D., Koeva, K. (2016), Artificial Intelligence technologies in human resource development, Computer Modelling and New Technologies, 20(2), 26-29.

Chang, N. (2010), The application of neural network to the allocation of enterprise human resources, 2010 2nd International Conference on E-Business and Information System Security, EBISS2010, 249--252. https://doi.org/10.1109/EBISS.2010.5473417

Chen, L.F., Chien, C.F. (2011), Manufacturing intelligence for class prediction and rule generation to support human capital decisions for high-tech industries, Flexible Services and Manufacturing Journal, 23(3), 263-289. https://doi.org/10.1007/s10696-010-9068-x

Chin, W.W. (1998), Issues and opinion on structural equation modeling, MIS Quarterly: Management Information Systems, 22(1).

Chiu, C.-Y., Chen, S., Chen, C.-L. (2017), An integrated perspective of TOE framework and innovation diffusion in broadband mobile applications adoption by enterprises, International Journal of Management, Economics and Social Sciences, 6(1), 14-39.

Chong, A.Y.L., Chan, F.T.S. (2012), Structural equation modeling for multi-stage analysis on Radio Frequency Identification (RFID) diffusion in the health care industry, Expert Systems with Applications, 39(10), 8645-8654. https://doi.org/10.1016/j.eswa.2012.01.201

Daramola, J.O., Oladipupo, O.O., Musa, A.G. (2010), A fuzzy expert system (FES) tool for online personnel recruitments, International Journal of Business Information Systems, 6(4), 444-462. https://doi.org/10.1504/IJBIS.2010.035741

Ellig, B.R. (1997), Is the human resource function neglecting the employees?, Human Resource Management, 36(1), 91-95. https://doi.org/10.1002/(sici)1099-050x(199721)36:1<91::aid-hrm15>3.3.co;2-u

Fornell, C., Larcker, D.F. (1981), Structural Equation models with unobservable variables and measurement error: Algebra and statistics, Journal of Marketing Research, 18(3), 382. https://doi.org/10.2307/3150980

Gardner, S.D., Lepak, D.P., Bartol, K.M. (2003), Virtual HR: The impact of information technology on the human resource professional, Journal of Vocational Behavior, 63(2), 159-179. https://doi.org/10.1016/S0001-8791(03)00039-3

Hair, J.F., da Silva Gabriel, M.L.D., 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), 44-55. https://doi.org/10.5585/remark.v13i2.2718

Hempel, P.S. (2004), Preparing the HR profession for technology and information work, Human Resource Management, 43(2-3), 163-177. https://doi.org/10.1002/hrm.20013

Huang, L.C., Huang, K.S., Huang, H.P., Jaw, B.S. (2004), Applying fuzzy neural network in human resource selection system, Annual Conference of the North American Fuzzy Information Processing Society - NAFIPS, 1, 169-174.

Jing, H. (2009), Application of fuzzy data mining algorithm in performance evaluation of human resource, IFCSTA 2009 Proceedings – 2009 International Forum on Computer Science-Technology and Applications, 1, 343-346. https://doi.org/10.1109/IFCSTA.2009.90

Kabak, M., Burmaoğlu, S., Kazançoğlu, Y. (2012), A fuzzy hybrid MCDM approach for professional selection, Expert Systems with Applications, 39(3), 3516-3525. https://doi.org/10.1016/j.eswa.2011.09.042

Lee, J. (2004), Discriminant analysis of technology adoption behavior: A case of internet technologies in small businesses, Journal of Computer Information Systems, 44(4), 57-66. https://doi.org/10.1080/08874417.2004.11647596

Lee, Y. T. (2010), Exploring high-performers' required competencies, Expert Systems with Applications, 37(1), 434-439. https://doi.org/10.1016/j.eswa.2009.05.064

Lin, H.F. (2013), Understanding the determinants of electronic supply chain management system adoption: Using the technology-organization-environment framework, Technological Forecasting and Social Change, 80-92. https://doi.org/10.1016/j.techfore.2013.09.001

Lin, H.T. (2010), Personnel selection using analytic network process and fuzzy data envelopment analysis approaches, Computers and Industrial Engineering, 59(4), 937-944. https://doi.org/10.1016/j.cie.2010.09.004

Lin, A., Chen, N.C. (2012), Cloud computing as an innovation: Percepetion, attitude, and adoption, International Journal of Information Management, 32(6), 533-540. https://doi.org/10.1016/j.ijinfomgt.2012.04.001

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

Martins, R., Oliveira, T., Thomas, M.A. (2016), An empirical analysis to assess the determinants of SaaS diffusion in firms, Computers in Human Behavior, 62, 19-33. https://doi.org/10.1016/j.chb.2016.03.049

Mehrabad, S.M., Brojeny, F. (2007), The development of an expert system for effective selection and appointment of the jobs applicants in human resource management, Computers and Industrial Engineering, 53(2), 306-312. https://doi.org/10.1016/j.cie.2007.06.023

Obeidat, S.M. (2016), The link between e-HRM use and HRM effectiveness: An empirical study, Personnel Review, 45(6), 1281-1301. https://doi.org/10.1108/PR-04-2015-0111

Oliveira, T., Martins, M.F. (2010), Understanding e-business adoption across industries in European countries, Industrial Management and Data Systems, 110(9), 1337-1354. https://doi.org/10.1108/02635571011087428

Oliveira, T., Thomas, M., Espadanal, M. (2014), Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors, Information and Management, 51(5), 497-510. https://doi.org/10.1016/j.im.2014.03.006

Panayotopoulou, L., Vakola, M., Galanaki, E. (2007), E-HR adoption and the role of HRM: Evidence from Greece, Personnel Review, 36(2), 277-294. https://doi.org/10.1108/00483480710726145

Premkumar, G., Ramamurthy, K. (1995), The Role of interorganizational and organizational factors on the decision mode for adoption of interorganizational systems, Decision Sciences, 26(3), 303-336. https://doi.org/10.1111/j.1540-5915.1995.tb01431.x

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

Puklavec, B., Oliveira, T., Popovič, A. (2018), Understanding the determinants of business intelligence system adoption stages an empirical study of SMEs, Industrial Management and Data Systems, 118(1), 236-261. https://doi.org/10.1108/IMDS-05-2017-0170

Ramdani, B., Kawalek, P., Lorenzo, O. (2009), Predicting SMEs' adoption of enterprise systems, Journal of Enterprise Information Management, 22, 10-24. https://doi.org/10.1108/17410390910922796

Rashid, T.A., Jabar, A.L. (2016), Improvement on predicting employee behaviour through intelligent techniques, IET Networks, 5(5), 136-142. https://doi.org/10.1049/iet-net.2015.0106

Sivaram, N., Ramar, K. (2010), Applicability of clustering and classification algorithms for recruitment data mining, International Journal of Computer Applications, 4(5), 23-28. https://doi.org/10.5120/823-1165

Sivathanu, B., Pillai, R. (2018), Smart HR 4.0 – how industry 4.0 is disrupting HR, Human Resource Management International Digest, 26(4), 7-11. https://doi.org/10.1108/HRMID-04-2018-0059

Straub, D.W. (1989), Validating instruments in MIS research, MIS Quarterly: Management Information Systems, 13(2), 147-165. https://doi.org/10.2307/248922

Strohmeier, S., Franca, P. (2015), Artificial Intelligence techniques in human resource management – a conceptual exploration, In: C. Kahraman, S., Çevik Onar (Eds.), Intelligent techniques in engineering management (pp. 149-172), Cham: Springer. https://doi.org/10.1007/978-3-319-17906-3

Strohmeier, S., Piazza, F. (2013), Domain driven data mining in human resource management: A review of current research, Expert Systems with Applications, 40(7), 2410-2420. https://doi.org/10.1016/j.eswa.2012.10.059

Sun, S., Cegielski, C.G., Jia, L., Hall, D.J. (2018), Understanding the factors affecting the organizational adoption of big data, Journal of Computer Information Systems, 58(3), 193-203. https://doi.org/10.1080/08874417.2016.1222891

Tai, W.S., Hsu, C.C. (2006) A realistic personnel selection tool based on fuzzy data mining method, Proceedings of the 9th Joint Conference on Information Sciences, JCIS 2006, 2006. https://doi.org/10.2991/jcis.2006.46

Teo, T. (2012), Examining the intention to use technology among pre-service teachers: An integration of the technology acceptance model and theory of planned behavior, Interactive Learning Environments, 20(1), 3-18. https://doi.org/10.1080/10494821003714632

Tung, K.Y., Huang, I.C., Chen, S.L., Shih, C.T. (2005), Mining the generation Xers' job attitudes by artificial neural network and decision tree – Empirical evidence in Taiwan, Expert Systems with Applications, 29(4), 783-794. https://doi.org/10.1016/j.eswa.2005.06.012

Ulrich, D. (1997), HR of the future, Human Resource Management, 36(1), 175-179. https://doi.org/10.1002/(SICI)1099-050X(199721)36:1<175::AID-HRM28>3.0.CO;2-9

Ulrich, D. (1998), A new mandate for human resources, Harvard Business Review, 76(1), 124-134.

Venkatesh, V., Morris, M.G., Davis, G.B., Davis, F.D. (2003), User acceptance of information technology: toward a unified view, MIS Quarterly, 27(3), 425-478.

Venkatesh, V., Thong, J.Y.L.T., Xu, X. (2012), Consumer acceptance and use of IT, MIS Quarterly, 36(1), 157-178.

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

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

Wang, Y.S., Li, H.T., Li, C.R., Zhang, D.Z. (2016), Factors affecting hotels' adoption of mobile reservation systems: A technology-organization-environment framework, Tourism Management, 53, 163-172. https://doi.org/10.1016/j.tourman.2015.09.021

Warshaw, P.R., Davis, F.D. (1985), Disentangling behavioral intention and behavioral expectation, Journal of Experimental Social Psychology, 21(3), 213-228. https://doi.org/10.1016/0022-1031(85)90017-4

Wu, W.W. (2009), Exploring core competencies for RandD technical professionals, Expert Systems with Applications, 36(5), 9574-9579. https://doi.org/10.1016/j.eswa.2008.07.052

Yang, Z., Sun, J., Zhang, Y., Wang, Y. (2015), Understanding SaaS adoption from the perspective of organizational users: A tripod readiness model, Computers in Human Behavior, 45, 254-264. https://doi.org/10.1016/j.chb.2014.12.022

Zhao, X. (2008), A study of performance evaluation of HRM: Based on data mining, Proceedings – 2008 International Seminar on Future Information Technology and Management Engineering, FITME 2008, 45-48. https://doi.org/10.1109/FITME.2008.133

Bilal Hmoud is a Ph.D. student at the Department of Business Informatics, Faculty of Economics and Business, University of Debrecen, Debrecen, Hungary. He received his master's degree in Human Resources Counselling from the University of Pécs, Pécs, Hungary. His current research interests pertain to the application of artificial intelligence in human resource management and the adoption thereof. He has over seven years of professional work experience in the human resource management field at regional level in the Middle East, specialising in the area of human resource management development. https://orcid.org/0000-0003-1685-7941