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THE DETERMINANTS OF HR LEADERS' ATTITUDE TOWARD THE ADOPTION OF ARTIFICIAL INTELLIGENCE IN HUMAN RESOURCES MANAGEMENT

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INTRODUCTION

The function of Human Resources Management (HRM) has had multiple transformations that reshaped its fundamental contribution at a micro-organizational level and the macroeconomics level. These transformations are observably lifting the HRM function upward toward an increased strategic weight. The HRM function was founded as a result of the emergence of the labour movement and legislation that addresses Human Resources (HR) rights, to regulate the relationship between employers and employees. Hence, the early conventional focus was directed toward handling personnel management and labour-union relationship. However, it is agreed that nowadays, and driven by the rapid changes in economics and business factors, HRM has a far more important role within the organizations and within the different segments, private or public, profit or non-profit. Globalization, information technology, social trends, political power, and competitiveness are among these factors that have had a major impact on HRM methodology and conduct. While all these factors are reportedly important, the digital transformation and its rapid development have had a wide and major effect in redefining most of the organizational functions among which, HRM. The contemporary economical changes in which driven by Information Technology (IT) innovations are far more intense and rapid if compared with other factors. The reason behind this distinctive effect is the reanimated nature of IT science. It develops so rapidly that several organizations and business sectors have been driven out of business for not keeping up. From an HRM perspective, it is quite clear that IT and the internet have had a major impact on reshaping the methods by which organisations are managing their HR. This rapidly changing IT environment and has had a profound reinvention of conventional HRM making it more technologically dependent. Moreover, redefine the HRM core competencies. The severity of these changes is very much connected to the IT innovations' characteristics. For instance, the early digitalizing of the HR function from conventional paperwork methods by the emergence of the Human Resources Information System (HRIS) have had a major role in reducing the administrative burden of HR tasks. Later, the invention of the internet has expanded its geographic exposure and improved the efficacy of HRM function by virtually connecting all the stakeholders through the emergence of Electronic Human Resources (e-HR).

HRIS and e-HR are among the most significant factors in which granted HRM its current strategically shifting importance and becomes inevitable for achieving organizations strategic goals throughout acquiring, develop, motivate and retain qualified talents in an increasingly competitive environment

(Strohmeier, 2007). Whereas there is no doubt about the substantial strategic impact in which HRIS and e-HR had particularly in communication, process efficiency, cost management, knowledge management, and HR branding, thus it mostly targeted tactical HR application. In other words, the mainstream of technological transformation in HRM have focused on handling administrative HR tasks to improve the efficient use of resources, save time and cost, elevate productivity, hence, gain competitive advantage. However, today's era of industry 4.0 in which we are experiencing is just overwhelming and radically distinct. Industry 4.0 refers to a new era of the Industrial Revolution that heavily relying on interconnectivity, automation, Artificial Intelligence (AI), machine learning, big data, and real-time data. This direction of relying on automation, connectivity, and AI is advancing dramatically and it is not going to hold back anytime soon. The private AI investments worldwide has reached $70 billion of which 37 billion are AI-related startup investments. Academically, 3% of peer-reviewed journal publications and 9% of published conference papers are related to AI (Perrault et al., 2019). It is not an argument anymore, this rapid reliance on machine learning and AI technologies is for sure altering jobs, functions, organization structure, and business conduct methods leading to an imperative competition. Nowadays, almost most of the organizational functions incorporating or considering adopting AI to produce a better result, for instance, engineering, telecommunication, customer service, financial services, healthcare, pharma, and medical production are among the highest AI-adopter's industries.

Whereas HRIS and e-HRM have had a key role in shaping the current models of HRM and have led to considerable changes within the HR domain, machine learning, and AI-based HR system are representing the future of processing HRM tasks and it is gaining increased focus. AI use in HRM has noticeably witnessed an increasing investment during the last five years. The utilization of AI in HRM represents a breakthrough in the traditional role of technology in HRM. The reason behind this perceived importance is that while HRIS and e-HR have tackled the HRM efficiency (time and cost) and inclusion phenomenon, smart AI-based HR applications promote augmented intelligence in which embodies a revolutionary essential uplift within the technology role in HRM by enabling humans and software's to jointly make decisions. Although HRIS and e-HR have reduced the administrative burden of HR and saved-time, however, its role was restricted to connecting HR stakeholders collecting and storing data to facilitate the decision-making process. For instance, for HR recruitment, HRIS and e-HR provided an electronic means for acquiring talents, thus, the candidates, communication, screening, shortlisting, and classifying require a human intervention which represents time-consuming and costly tasks. AI HR applications have provided smart HR solutions in which applies machine learning and other AI tools to autonomously process such time-consuming and costly HR tasks. Similar to e-HR, augmented intelligence through the use of AI tools is considered another distinctive elevation of IT role within HRM and will significantly affect the HRM conduct and core competencies. Chatbots, intelligent search engines, smart Applicant Tracking Systems (ATS), virtual reality-based learning systems, analytical systems are examples of trending AI implementations in HRM. Besides time and cost-saving, the additional potential value of AI-based HR solutions is that it promises of immense contribution to HRM quality too. For instance, instantaneous services provide and maintaining consistent communication with HR stakeholders through Chatbots and Candidate Relationship Management (CRM) software are connected with higher customer satisfaction and employer branding. Moreover, human mistakes and bias, are among the main HR challenges that AI have claims to eliminate. While the greatest share of these smart HR solutions was directed toward the HR recruitment and selection function to optimize the talent acquisition process, others were oriented toward HR development, compensation, employee relations, and other function as well.

IT innovation acceptance and adoption have received noticeable attention from IT research literature. From an HRM perspective, most of the research has approached the phenomenon of IT application in HRM from two key standpoints. The first tried to investigate the actual impact to which IT had on HRM roles, efficiency, and effectiveness. This contribution of the research is usually associated with the post-diffusion phase. The second tried to explore and define the several significant factors of which associated with the IT innovation acceptance and adoption decision. To achieve this purpose, researchers have applied a variety of IT innovation adoption and acceptance models within the HRIS context (Ball, 2001; Strohmeier & Kabst, 2009). HRIS and e-HRM applications and adoption have received a considerable amount of research attention (Florkowski & Olivas-Luján, 2006; Kovach et al., 2002; Kovach & Cathcart, 1999; Ngai & Wat, 2004; Strohmeier, 2007; Voermans & Van Veldhoven, 2007), thus, research in which addressing the phenomenon of AI and machine learning applications, impact and adoption in HRM are limited. While AI applications in HRM promise a fundamental change within its functionalities in which consistent with industry 4.0, research connected to its adoption factors, the organizations and HR practitioners' attitude toward its use noticeably scarce. Therefore, this research identifies four research gaps in which associated with AI acceptance and adoption in HRM. First, is the influence of AI innovation characteristics (Rogers,

2003) on HR practitioners' attitude toward adopting AI in HRM. For instance, to what extent does the perceived relative advantage, compatibility, or complexity predict the negative or positive attitude toward AI. The sconed identified research gap is the trust factor. While surveys initially indicate that more executives and organizations perceive the value-added of adopting AI, yet HR practitioners' trust is still under debate. Trust is a very crucial factor in which appeared frequently within IT adoption research (Kim et al., 2009; Lippert & Davis, 2006; Parasuraman et al., 2008), thus, there a significant gap in the empirical investigation of the technology trust factor in predicting AI adoption behaviour. The defined third research gap is the relationship between technological, organizational, and environmental construct, specifically firm size, top management support, and technological readiness with HR practitioners' attitude toward adopting AI applications in HRM. Lastly, the fourth research gap of which addressed by this research is the relationship between the emphasized HR roles within the organization with HR practitioners' attitude toward adopting AI applications in HRM.

Limited empirical research has been carried out to evaluate the factors of which influence the adoption of AI in HRM. However, to the best of my knowledge, the identified research gaps have not been investigated previously. Therefore, propelled by my belief that visible sweeping direction toward AI-based businesses operation will eventually broadly manifests within the HRM function in near future, this research is an effort to fills the research gap within the AI adoption in HRM.

1. TOPICS AND OBJECTIVES

1.1. RESEARCH AIMS

This research is an attempt to fill the research gap in the adoption and acceptance of AI and smart applications in HRM. It aims to contribute to the technology adoption research area by providing the researchers, organizations, HR leaders, service providers, and policymakers with advanced understanding and valid inputs about AI-based HR solutions development and adoption determinants.

1.2. RESEARCH OBJECTIVES

The key objectives of this research are as follows:

1. Develop a thorough conceptual framework model to evaluate the influence of which research factors have with HR leaders toward the adoption of AI in HRM.
2. Identify the general attitude of HR leaders toward the adoption of AI in HRM.

3. Understand the relationship between the AI tools innovation characteristics and the HR leaders’ attitude toward its adoption.
4. Evaluate the influence of technology reliability, credibility, and technological competence on HR leaders' trust in AI usage within HRM.
5. Evaluate HR leaders Trust in AI-based technology and its relationship with their attitude toward its adoption.
6. Assess the influence between predefined specific technological, organizational, and environmental factors namely: firm size, technological readiness, top management support, and competitive pressure on HR leaders’ attitude toward the adoption of AI in HRM.
7. Investigate the relationship between the emphasized HR-Roles within the organization and the HR leaders’ attitude toward the adoption of AI in HRM.

1.3. RESEARCH QUESTIONS

This research attempts to attain the previously listed objected by answering the following research questions:

1. What is the perception and attitude of HR leaders toward adopting AI within HRM?
2. What is the relationship between AI-based HR applications innovation characteristics such as relative advantage, complexity, and compatibility with HR leaders’ attitude toward the adoption of AI in HRM?
3. What are the main determinants of AI technology trust from HR leaders’ perspective?
4. To what extent do HR leaders trust AI in processing their HRM tasks and what relationship it has with their attitude toward it?
5. What is the association between firm size, technological readiness, top management support, and competitive pressure on HR leaders’ attitude toward the adoption of AI in HRM?
6. What is the relationship between the emphasized HR-Roles within the organization and the HR leaders’ attitude toward the adoption of AI in HRM?

2. BACKGROUND

2.1. AI TECHNIQUES IN HRIS LITERATURE

Tracing the literature, it is noticeable that AI research in HRIS started as early as the beginning of this century and it has mainly focused on exploring theoretical possible applications of AI in HRM. The development in algorithms, knowledge-based search engines, data mining, expert system, Artificial Neural Network (ANN), machine learning, and others (Lucci & Kopec, 2016), has induced researchers to investigate its potential contribution to HRIS. Expectedly, researchers had proposed models and intelligent systems that support the HR decision-making process. Akin to HRIS and e-HR, the early literature of AI application in HR systems had been directed toward tactical time-consuming HR applications especially within recruitment and selection function where AI technology was perceived as a prospect to propose solutions to improve the hiring process efficiency and job matching. Thus, Researchers have explored AI application in several HR functionalities and a heterogeneous of AI research have emerged explaining how certain AI techniques could be utilized for specific HR tasks. Table 1. summarizes the literature on AI techniques in HR based on the HRM domain.

Table 1. Summary of AI Techniques in HR literature

HRM Domain	Task Domain	AI Techniques and literature
HR Sourcing	Match jobs with job seekers. Extract the matching candidates, Resumes information extraction.	Knowledge-based search engines (Mochol et al., 2007; Strohmeier & Franca, 2015) Information Extraction (Çelik, 2016)
Applicants Evaluation, Selection and Allocation	Assessment of job applicants. Classify applicants. Filter fitted candidates from a large volume of the applicant pool. Predict future performance. Discover implicit knowledge. Human resources allocation to proper positions and projects.	Data Mining (Dursun & Karsak, 2010; Strohmeier & Franca, 2015). Fuzzy Logic (Dursun & Karsak, 2010; Golec & Kahya, 2007; Kabak et al., 2012; Lin, 2010). Fuzzy Data Mining (L. F. Chen & Chien, 2011; Dursun & Karsak, 2010; M. J. Huang et al., 2006; Sivaram & Ramar, 2010; Tai & Hsu, 2006). Expert System (Daramola et al., 2010; Mehrabad & Brojeny, 2007). ANN (Chang, 2010; Dwivedi et al., 2019; L. C. Huang et al., 2004; M. J. Huang et al., 2006; Thissen-roe, 2005; Tung et al., 2005). Machine Learning (Hsu et al., 2019; Mahmoud et al., 2019).

Turnover Prediction	Analyzing demographics Withdrawal behaviours Predict absenteeism Social scanning	Data Mining (Nagadevara & Srinivasan, 2007). ANN (Ali Shah et al., 2020; Sexton et al., 2005; Soni et al., 2019; Strohmeier & Franca, 2015) Machine Learning (Punnoose & Ajit, 2016; Zhang et al., 2018; Y. Zhao et al., 2018).
Human Resources Development (HRD)	Intelligent tutoring systems. log file and clickstream. Virtual reality-based learning systems. Games and Simulations. Capture learner's semantics. Voice recognition. Training-Learner matching. Extract learner input	Data Mining (K. K. Chen et al., 2007; Cope et al., 2020). Expert System (K. K. Chen et al., 2007). Natural language (Cope et al., 2020; Strohmeier & Franca, 2015). Genetic Algorithm (Giotopoulos et al., 2006).
Performance Management (PM)	Assess the employee's performance. Identify employees core competencies. Evaluate workforce productivity and effectiveness. Define organization competence ontologies	Data Mining (Jing, 2009; Rashid & Jabar, 2016; X. Zhao, 2008). Rough Set Theory (Lee, 2010; Wu, 2009). ANN (Azadeh & Zarrin, 2016).

Source: Author's Construction

2.2. TRENDING AI APPLICATIONS IN HRM AND EMERGENT THEMES

It is noticeable that the sourcing function is among the first other HR functions in which incorporated AI within its process to automate candidates' search and matching process. Nowadays, the recruitment industry has noticeably proliferated, where the conventional hiring process with resumes and job advertising is diminishing in favour of the reliance on Professional Networking Platforms (PNPs) or other online outsourcing means for talent acquisition. PNPs provide users and recruiters with a more dynamic approach to represent themselves, gain further information, and multi-source feedback about each other (Zide et al., 2014). For example, LinkedIn professional network has currently more than 722 million users and according to Society of Human Resource Management (SHRM) Survey with 541 HR professionals, 95 per cent revealed that they use LinkedIn to source passive talents who might not otherwise apply for the job (Zide et al., 2014). At Present, AI powers everything at LinkedIn, for instance, machine learning models to create relationships between job titles and deep learning to capture users' preferences and produce personalization (Agarwal, 2018).

Another tool is AI-powered Applicant Tracking Systems (ATS) which provides recruiters with the opportunity to conduct instantaneous talents search based on the defined job requirements. Surveys show that 90% of large companies and 68% of small and medium-sized companies users are using ATS and it represents the biggest share of the recruitment industry (Mondal, 2020). For example "Beamery" and "Workable", an AI-based self-styled recruitment marketing software that read the vacant specification and employs data mining algorithms and other AI techniques to conduct online screening throughout social media and PNPs to locate active and passive and notify matching result about the new vacant (Dickson, 2017). "Taleo", another ATS, in which acquired by Oracle for $1.9 billion, and it is considered the leading recruiting software in the ATS category with 23% of market share (Mondal, 2020). Once talents were sourced, assessment, shortlisting, and selection are the next tasks within the talent acquisition process. However, the conventional screening and short-listing process in which relies on HR personnel assessing, testing, and selecting a candidate from a large number of talents, is a challenging and very time-consuming task. While it varies according to the job specification, the average number of sourced talents could range from a few numbers to hundreds or thousands. Contemporary AI-based talent assessment tools facilitate talent assessment by facilitating the shortlisting process to reduce this number into the desired number. One of the tools that facilitate the screening and testing process is candidate relationship management (CRM) software, for instance, chatbots. Chatbots highly feasible tool which heavily invested within the recruitment industry. After learning the job specification, chatbots are AI-based tools that autonomously review candidates' qualities, hold conversations with them, assess their suitability, gather additional information if needed, classify, and guide them through the process (Balachandar & Kulkarni, 2018; Burgess & Burgess, 2018).

Additional to saving time, Chatbot provides instantaneous contact with applicants in a consistent manner in which neutralizes human judgmental errors and biases. Chatbots offers a comprehensive of hiring services in which it can be integrated into ATS and HRIS, once the application is received, chatbots will autonomously screen the applicant profile against the job specification, initiate instant contact with the applicant to guide them through the hiring process, and perform screening interview. Apart from the screening process, Chatbots can perform a variety of predefined assessment tests and gather additional information if needed. "Mya", "HireVue" and "Wendy" are examples of common AI-based HRM Chatbots (Raub, 2018). For instance, "Mya" offers the opportunity to automate 75% of the talent acquisition process (Dickson, 2017). It employs intelligent neural language and machine learning techniques to autonomously provide candidate relationship management in which includes, provide applicants with feedback, detect gaps in a resume and poses detailed follow-up contextual questions, allow candidates to further explicate how they fit for the job, and accordingly rank candidates based on a comprehensive assessment. Mya keeps candidates updated and throughout the hiring process, alerts applicants about additional suitable vacancies, and handle administrative tasks such as phone screening, interview scheduling, and onboarding (Delliots, 2018; Hmoud & Laszlo, 2019). These chatbots operate with machine learning capability and whenever the answer is missing, it will refer the question to HR personnel and preserve the information (Hmoud & Laszlo, 2019).

Other AI-based solutions (eg. “Affectiva”, “HireIQ”, “HireVue”) are used in assessing candidates throughout the interview by using facial expression analysis and emotion extract techniques (Boz & Kose, 2018). For instance, “HireVue” CRM software in which analyzes interviews, records facial expressions and word choices to provides recruiters with an assessment of candidate’s levels of engagement, motivation, honesty, personality, and energy. HireVue algorithms are trained on data from the firm, incorporates Industrial-Organizational Psychology, and assess the candidates compared to the client's top performers (Tambe et al., 2018). Also, background check is another hiring task in which traditional methods requires time and effort, AI software such as “FAMA” which uses natural language automates this process by scanning the internet, news, social media, blogs, and PNPs and extract available information about applicants criminal history, violence, drug abuse, workplace misconducts, positive indicators such as volunteering, and other relevant information (Mahmoud et al., 2019).

2.3. Potential Impact on HRM Quality

Several advantages in terms of talent acquisition overall efficiency and effectiveness are behind the growing recent investment in the AI-based recruitment industry. If compared with traditional HRIS, AI has elevated the technology contribution to talent acquisition into a new level of augmented intelligence where software runs with minimum human intervention. Instantaneous candidate sourcing, screening, and matching process which were considered the most time-consuming process have significantly saved time, and shortened the time needed for hire, thus, enhance the organisation's ability to fill skills gaps and vacancies faster. From cost-wise, filling vacant faster reduces the operational cost associated with HR shortage. Additionally, taking over repetitive tasks will provide HR personnel with an opportunity to shift focus toward other important tasks, thus reduces the cost per hire. Moreover, what is noticeable that the trend in these AI-solution is that unlike traditional HRIS it charges per time-used and runs in could-based methods, which eliminate the existence of fixed costs such as hardware installation and system maintenance (Yawalkar, 2019).

Additional to time and cost, AI improves hiring process quality and organization branding. For instance, the AI candidates screening process argues to guarantee a fair, accurate, unbiased, and inclusive process. Besides, studies have shown that lack of communication and feedback is among the major factors that cause applicants' negative perception about the organization, and in the opposite, instant services are greatly connected with customer satisfaction (Adam et al., 2020), therefore, Candidate experience is a vital aspect of the hiring process. Talent acquisition Chatbots have a significant role in improving the candidate's satisfaction by keeping them informed about their application status throughout the process which eliminates the communication gap between recruiters and the candidates, thus, enhance employers' image and brand.

3. CONCEPTUAL FRAMEWORK

To achieve the research objectives, the research focus was fluctuating between initially focus on internal dynamics and business processes, internet emergence and the shift to external factors, and power of individual perception. To gain a comprehensive increased understanding of the research topic a valid conceptual framework has been developed to direct the research effort toward achieving the research objectives. The conceptual framework represents provide an integrative overview that attaches the factors in which are hypothesized to have a relationship with HR Leaders' attitude toward the adoption of AI applications in HRM. The investigated factors fall into the following four main constructs:

1. Innovation Characteristics
2. Technology-Organization-Environment (TOE)
3. Technology Trust
4. HR-Roles

The study constructs are selected based on their perceived influential importance on HR Leaders' attitudes towards the adoption of AI in HRM. The fact the AI diffusion within HRM is still at the early knowledge and persuasion diffusion stage and in alignment with previous studies in which underlined that during early diffusion stages with low external pressure, the higher emphases is on internal constructs (Rogers, 2003). Therefore, apart from competitive pressure, the main focus of the study is on examine innovation characteristics factors, individuals trust in technology, and internal organization structure. The proposed conceptual framework represented below (Figure 1) is developed to understand and investigate the predicted relationships of these factors and the influence of the proposed variables on HR Leaders' attitude toward adopting AI applications in HRM. It is believed that this conceptual framework will best serve the research objectives. This conceptual framework is grounded on the theoretical foundations from recognized previously verified IT innovation diffusion theories namely, Diffusion of Innovation Theory (DOI), and Technology-Organization-Environment (TOE) framework, and (Ulrich, 1997) HR-Roles theory. It is important to site that all factors in which identified in this study are suggested by the previous literature and were used before to explain well-established IT diffusion research. However, there was no agreement on their importance rank and results showed that their importance has varied when compared between the different research contexts.

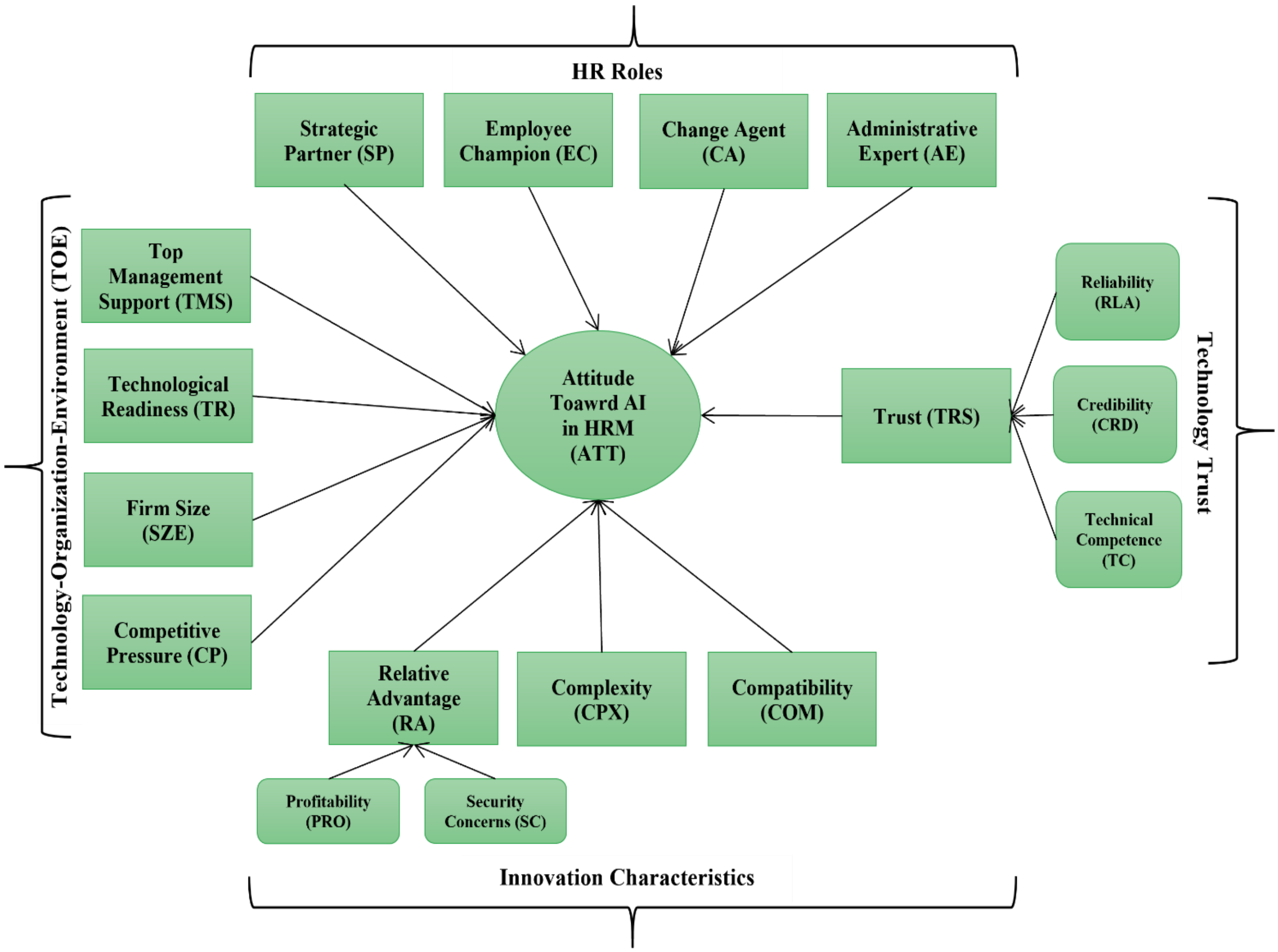

Figure 1: Research Conceptual Framework
Source: Author's Construction

4. RESEARCH METHODS

This research aims to provide empirically supported evidence in the predictive power of a predefined set of factors on HR Leaders' attitude toward the adoption of AI in HRM. to achieve this purpose, this research poses research questions in which interrelate and guide the applied research methods. A conceptual framework is introduced to guide the factual measurement of the variables and investigate the theoretical facts underlying hypothesized relationships. This research aims to investigate the hypothesized relationships; therefore, this is an exploratory study that adopts a positivism research paradigm and utilizes a deductive quantitative methodology. This research is built on primary and secondary data. The used Secondary data for this research were mostly in form of written documentary literature (e.g., reports, journals article, and books, annual reports) that related to the research area. An online questionnaire (see Table 2) is used to collect this research primary data from HR leaders in Middle East Countries, specifically: Jordan, Kuwait, Saudi Arabia, and Qatar. This research used a systematic disproportionate stratified random sampling and a 389 sample size. Data is analyzed to test the research conceptual model using several statistical techniques among which, descriptive data analysis, exploratory factor analysis, reliability analysis, regression appropriateness analysis, and multiple regression analysis.

Table 2: Instrument Measures

Construct	**Variables**	**Number of Items**	**Scale of Measurement**	**Based on (sources)**
Classifications	Country of Employment	1	Multiple options	Own Construct
	Age	1	Multiple options	(Ngai & Wat, 2004)
	Academic Level	1	Multiple options	(Ngai & Wat, 2004)
	Experience		Multiple options	(Ngai & Wat, 2004)
	Job Title	1	Multiple options	Own Construct
Total		4		
Innovation Characteristics	Compatibility (COM)	4	Likert Scale (1= Strongly disagree; 5= strongly agree)	(Oliveira et al., 2014)
	Relative Advantage (RA)	5		(Martins et al., 2016; Teo et al., 2007)
	Complexity (CPX)	4		(Martins et al., 2016; Wang et al., 2016)
	Profitability (PRO)	3		(Martins et al., 2016; Oliveira et al., 2014)
	Security Concerns (SC)	3		(Martins et al., 2016; Oliveira et al., 2014)
Total		19		
Technological Organizational Environmental (TOE)	Top Management Support (TMS)	4	Likert Scale (1= Strongly disagree; 5= strongly agree)	(Palos-Sanchez et al., 2017; Wang et al., 2016)
	Technological Readiness (TR)	4		(Martins et al., 2016; Oliveira et al., 2014)
	Firm Size	2	Multiple options	(Oliveira et al., 2014; Teo et al., 2007)
	Competitive Pressure (CP)	4	Likert Scale (1= Strongly disagree; 5= strongly agree)	(Oliveira et al., 2014; Teo et al., 2007)
Total		14		
Trust	Reliability (RLA)	4	Likert Scale (1= Strongly disagree; 5= strongly agree)	(Choi & Ji, 2015; Thatcher et al., 2011)
	Credibility (CRD)	4		
	Technical Competence (TC)	4		
	Trust (TRS)	3		
Total		15		
HR Roles	Strategic Partner (SP)	5		(Ulrich, 1997)

	Administrative Expert (AE)	5	(1 is very low; 5 is very high)	
	Employee Champion (EC)	5		
	Change Agent (CA)	5		
Total		20		
Attitude Toward AI adoption	Attitude (ATT)	6	Likert Scale (1= Strongly disagree; 5= strongly agree)	(Venkatesh et al., 2003; Voermans & Van Veldhoven, 2007)
Overall Total		78		

Source: Author's Construction

5. RESEARCH FINDINGS AND THEIR EVALUATION

The analysis involved data alteration, transforming and evaluation using SPSS 25 software to produce meaningful results that answer the research questions. To achieve the research objectives several statistical analyses are applied, at first, a demographics analysis description is produced to describe the basic features of the data in the research and provide a snapshot of the respondent's demographic characteristics. The next step was to assess the instrument validity and reliability, to do so, the sample appropriateness and adequacy for factor analysis have been analyzed through assessing the items, Communalities, Kaiser Meyer Olkin (KMO), and total variance explained have been measured. After confirming adequacy, factor analysis is performed using Principal Component Analysis (PCA) where component analysis and common factor analysis is performed to assess the instrument validity. Eight items had to be removed and Administrative Expert Variable (AE) had the most negative impact in terms of gross loading on several factors, the whole variable had to be removed to acquire acceptable validity results for the research items. After the elimination of validity problems, all scale measures have met the standardized acceptable factor loading. Besides, convergent validity is supported by demonstrating the high reliabilities of scales in measuring the constructs. All research variables Cronbach's alpha measures have met the acceptable level of Cronbach's alpha measure, hence supporting Convergent validity.

Moreover, before conducting a regression analysis to test the research hypothesized predicted relationships. Several assumptions have been examined to assess the appropriateness of regression analysis on the collected data, specifically normality, Multicollinearity, and homoscedasticity (Hair et al., 2014).

5.1. REGRESSION ANALYSIS: TESTING RESEARCH HYPOTHESES

Predictors of Relative Advantage: A stepwise multiple regression analysis was carried out to assess the relationship between the predictors of Profitability (PRO) and Security Concerns (SC) with the predicted dependent variable of Relative Advantage (RA). Both predictor variables, Profitability and Security Concerns are significant predictors of Relative advantage. While profitability appears to be significantly positively related to relative advantage, the security concern has a significant negative relation with relative advantage. Table. 3 presents the results of the stepwise regression analysis which shows that the adjusted square for both predictors is .652 in which indicates that 65% of the variance in relative advantage can be explained by these two factors. However, among the two predictors profitability has shown to be the most important predictor of relative advantage with an adjusted R square of 0.638.

Table 25: Predictors of Relative Advantage Coefficients[a]

Factor	Unstandardized Coefficients		Standardized Coefficients	R Square	Adjusted R	R Square Change	t	Sig.
	B	Std. Error						
Profitability	0.767	0.029	0.788	0.639	0.638	0.638	26.148	0.000
Security Concerns	-0.098	0.025	-0.116	0.652	0.650	0.013	-3.860	0.000

a. Dependent Variable: RELATIVE_ADVANTAGE

Predictors of Trust: A stepwise multiple regression analysis was carried out to assess the relationship between the predictors of Reliability (RLA), Credibility (CRD) and Technological Competence (TC) with the predicted dependent variable of Trust (TRS). **A**ll predictor variables found to be a significant positive predictor of the Trust construct. TC and RLA at p=0.000 while CRD at p=0.05. Moreover, the overall adjusted square for the predictors is 0.765 which indicates that 76.5% of the variance in the Trust construct can be explained by these factors (See Table 4) However, ranking wise, technological competence is shown to be the most significant predictor of trust with an adjusted R square of 0.732. The second predictor in terms of importance is reliability and lastly is credibility.

Table. 4: Predictors of Trust Coefficients[a]

Variables	Unstandardized Coefficients		Standardized Coefficients	R Square	Adjusted R Square	R Square Change	t	Sig.
	B	Std. Error	Beta					
Technical Competence (TC)	0.587	0.057	0.527	0.732	0.732	0.732	10.338	0.000
Reliability (RLA)	0.293	0.061	0.250	0.763	0.762	0.030	4.769	0.000
Credibility (CRD)	0.150	0.059	0.139	0.767	0.765	0.004	2.549	0.011
a. Dependent Variable: TRUST								

Source: Author's Construction

Predictors of Attitude Toward the Adoption of AI in HRM: A multiple regression analysis was carried out to assess the relationship between the predictors of Relative Advantage (RA), Compatibility (COM), Complexity (CPX), Technological Readiness (TR), Competitive Pressure (CP), Top Management Support (TMS), Trust (TRS), Strategic Partner (SP), Change Agent (CA), Employee Champion (EC), and Size (SZE) with and the predicted dependent variable of Attitude (ATT). Table 5 shows the results of the multiple regression analysis which indicates that among the predictor variables, only three are a significant predictor of the attitude toward the adoption of AI in HRM. Namely, relative advantage, complexity, and trust. While relative advantage and trust appear to have a significant positive relation with attitude, complexity poses a significant negative relation with attitude. The β value ranged from the highest at 0.504 for the trust factor to the lowest at 0.004 for the change agent HR role. To fatherly investigate the predictors adjusted R square, a stepwise regression was processed (see Table 6).

The overall adjusted square for the predictors is 0.458 which indicates that 45.8% of the variance in the Attitude (ATT) construct can be explained by these three factors. However, importance ranking wise, Trust shown to be the most significant predictor of ATT with an adjusted R square of 0.404. The second predictor in terms of importance is Complexity and lastly is Relative Advantage. The size (SZE) predictor demonstrated a strong relationship with the dependent variable ATT with $\beta=0.52$, however not significant at $p=0.05$ level. Similarly, Compatibility (COM) and Top management support (TMS) variables did reflect a relationship with the dependent variable ATT with $p=0.073$ and $p=0.076$ respectively, however also not significant at $p=0.05$ level.

Table 5: Predictors of ATTITUDE Coefficients[a]

Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
SIZE	0.060	0.031	0.075	1.953	0.052
COMPATIBILITY	-0.090	0.050	-0.084	-1.798	0.073
RELATIVE ADVANTAGE	0.243	0.065	0.204	3.758	0.000
COMPLEXITY	-0.179	0.049	-0.142	-3.646	0.000
TOP MANAFEMENT SUPPORT	0.071	0.040	0.077	1.777	0.076
TECHNOLOGICAL READINESS	-0.015	0.050	-0.013	-0.295	0.768
COMPETITIVE PRESSURE	0.044	0.046	0.041	0.964	0.336
TRUST	0.570	0.062	0.504	9.237	0.000
STRATEGIC PARTNER	0.005	0.051	0.005	0.100	0.920
CHANGE AGENT	0.004	0.056	0.004	0.065	0.948
EMPLOYEE CHAMPION	0.009	0.047	0.009	0.184	0.854
a. Dependent Variable: ATTITUDE					

Source: Author's Calculation

Table 6: Predictors of ATTITUDE Model Summary[d]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics		
					R Square Change	F Change	Sig. F Change
1	.637[a]	0.406	0.404	0.64919	0.406	264.291	0.000
2	.662[b]	0.438	0.435	0.63204	0.032	22.286	0.000
3	.680[c]	0.462	0.458	0.61919	0.024	17.193	0.000
a. Predictors: (Constant), TRUST b. Predictors: (Constant), TRUST, COMPLEXITY							
c. Predictors: (Constant), TRUST, COMPLEXITY, RELATIVE_ADVANTAGE							
d. Dependent Variable: ATTITUDE							

Source: Author's Calculation

The Research hypotheses results are summarized in below Table 7.

Table 7: Results Summary of Hypotheses Test

1. Innovation Characteristics	**Results**
H1.1: Profitability has a significant positive influence on the HR leaders' perception of AI Relative Advantage.	**Supported**
H1.2: Technology Concerns has a significant negative influence on the HR leaders' perception of AI Relative Advantage.	**Supported**
H1.3: Relative Advantage has a significant positive influence on the HR leaders' attitude toward the adoption of AI in HRM.	**Supported**
H1.4: Compatibility has a significant positive influence on the HR leaders' attitude toward the adoption of AI in HRM.	**Rejected**

H1.5: Complexity has a significant negative influence on the HR leaders' attitude toward the adoption of AI in HRM.	**Supported**
2. Technology-organization-Environment (TOE)	
H2.1: Top Management Support has a significant positive influence on the HR leaders' attitude toward the adoption of AI in HRM.	**Rejected**
H2.2: Technological Readiness has no significant influence on the HR leaders' attitude toward the adoption of AI in HRM.	**Supported**
H2.3: Firm Size has a significant positive influence on the HR leaders' attitude toward the adoption of AI in HRM.	**Rejected**
H2.4: Competitive Pressure has a significant positive influence on the HR leaders' attitude toward the adoption of AI in HRM.	**Rejected**
3. Technology Trust	
H3.1: Technical competence has a significant positive influence on HR leaders' trust in AI-HR solutions.	**Supported**
H3.2 Reliability has a significant positive influence on HR leaders' trust in AI-HR solutions.	**Supported**
H3.3 Credibility has a significant positive influence on HR leaders' trust in AI-HR solutions.	**Supported**
H3.4 Trust has a significant positive influence on the HR leaders' attitude toward the adoption of AI in HRM.	**Supported**
4. HR-Roles	
H4.1: Strategic Partner HR role has a significant positive influence on the HR leaders' attitude toward the adoption of AI in HRM.	**Rejected**
H4.2: Administrative Expert HR role has a significant positive influence on the HR leaders' attitude toward the adoption of AI in HRM.	**Not tested**
H4.3: Employee Champion HR role has a significant positive influence on the HR leaders' attitude toward the adoption of AI in HRM.	**Rejected**
H4.4: Change Agent HR role has a significant positive influence on the HR leaders' attitude toward the adoption of AI in HRM	**Rejected**

Source: Author's Construction

6. CONCLUSIONS AND RECOMMENDATIONS

A conceptual framework was developed to better reflects the structural hypothesized relationships between the research constructs factors and founding a ground base theoretical model in which guides the research processes. A final overall review for the research framework is presented in below Figure 2, accepted research hypotheses are distinguished with colours.

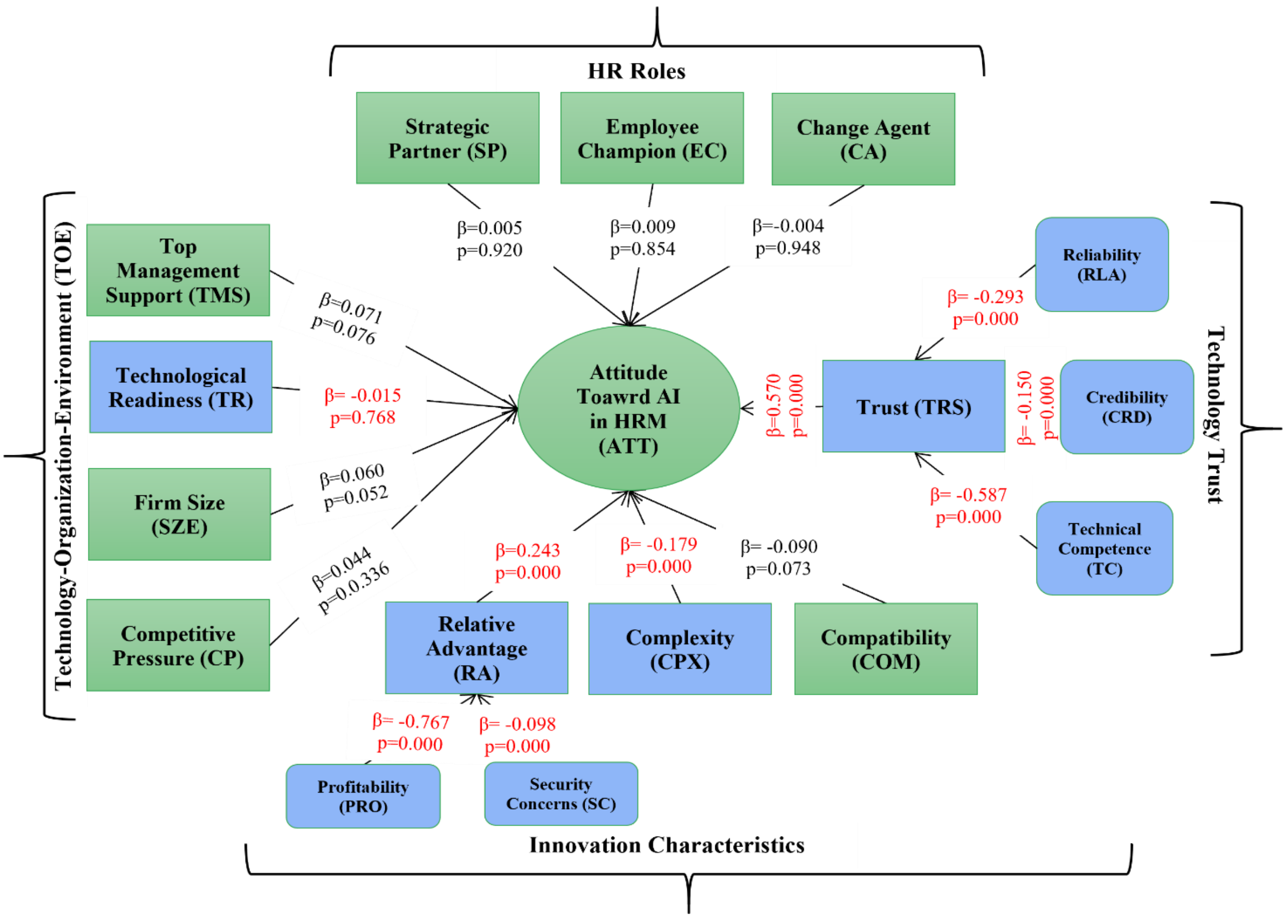

Figure 2: Research Framework Findings Review
Source: Author's Construction

The research analytical results have revealed that respondents expressed a high positive attitude toward emerging AI applications in HRM. This positive attitude is concluded from the mean result of two variables of Relative Advantage (RA) and Attitude toward AI in HRM (ATT) answers the first research question. Although that respondent did not convey a high level of pressure from competitors to adopt or accept AI applications in AI thus, they have expressed a positive attitude toward it. This supports the IT adoption literature that technological advancements are highly valued by organizations. This research concludes that HR leaders see IT innovations as highly advantageous and an opportunity to improve the efficiency and quality of HRM roles within the organization. Considering the strong repetitively proved the association between attitude and actual adoption behaviour within IT adoption research, it indicates that HRM AI applications will increasingly manifest within HRM function, hence significantly affects its practices and methods. This is congruent with the curving conduct within other sectors toward reliance on AI and machine learning to produce better results and congruent with the AI investment index which reveals that $70B in which $37B AI-related startup investments with annual growth of 48% (Perrault et al., 2019). Thus, the impact on HRM roles and competence needs investigation.

The research results have emphasized the role of innovation characteristics in predicting HR leaders' attitude toward the adoption of AI applications in HRM. Besides presenting a confirmative reference to the previously provided empirical evidence, this research conclusions provide variable input to policymakers and IT service providers about the significance of innovation characteristics. Cost-saving and security concerns are strongly important to promote the advantage of AI applications in HRM. While Profitability gained from saving the cost associated with HRM processes is important to attract HR leaders and organization attention toward its adoption, the higher security concerns will hinder its adoption. Therefore, service providers must realize that within this early diffusion phase, it is important to promote and give high attention to the data security and privacy factor of emerging AI HR tools. Besides, promoting profitability and security, a second input for service providers and policymakers is that the strongest innovation characteristic in which will affect HR leaders' attitude toward AI is its perceived relative advantage. They must focus on highlighting the gained benefits in terms of efficiency, effectiveness, and quality. In other words, the practical demonstration of the promised outcomes and overall process improvement to the decision-maker is highly associated with gaining their positive attitude toward the introduced AI innovations. It was concluded that normative compatibility represented with organization culture, norms, and work style has no significant effect on attitude toward AI. Another conclusion which represents a third variable input for organizations, service providers, HR leaders, and policymakers is the extent of complexity in determining AI adoption in HRM. The main conclusion is the complexity will hinder its adoption. Therefore, whomever promoting the inclusion of AI in HRM (HR leaders or service providers) must reduce the level of complexity for the decision-maker. While this relies heavily on the technical IT background of the adopter and seems a hard task when the adopter possesses lower IT skills, hence, simplifying the technical aspects of AI applications is a significant predictor of its acceptance. In other words, the extent of potential adopters understanding of how the output is produced, the AI data processing methods, the assurance of process legitimacy, and its use simplicity will significantly affect the acceptance of AI applications. These conclusions about innovation characteristics factors answer the second research question.

The research posed a question about technology trust aiming to understand the determinant of trust and the relationship of trust with attitude toward AI. The research findings constitute a valuable input for policymakers and service providers about the three defined determinants of technology trust (reliability, credibility, technical competence) within this research context. Based on these findings, it has been concluded that the higher capability of AI application to prove consistency and predictability in producing outputs, the more trusted by HR leaders. Additionally, the extent to which AI outputs are free from the implications of the conventional method such as bias, errors, and scepticisms, is also an important determinant of its trust. Further, the functional capability of AI application which means its ability to process the HRM tasks completely without excluding any task and produce the desired outcomes by the potential adopters also important. All these three determinants are concluded to be essential to maintain trust in AI. Further, it is concluded that HR leaders have relatively high trust in AI applications. This confirms the general assumptions about the increasing indicators of technology trust amongst the economic factors. moreover, among research investigated predictors of attitude toward the adoption of AI application in HRM, it is concluded that technology trust is the strongest predictor. These conclusions answer the third and fourth research questions.

From the technology trust perspective, a further investigation of HR leaders and organizations trust in the specific AI intervention is recommended. While this research reflected the general positive trust attitude toward AI, however, it is important assessing the level of trust in terms of the level of autonomous processing of HR tasks. For instance, if HR leaders would trust AI applications to source and categories applicants, would they trust AI applications to autonomously interview job applicants and produce AI-based evaluation or ranking or produce evaluative feedback for face-to-face interviews based on facial and voice analysis techniques. Accordingly, HR leaders are recommended to define the acceptable level of autonomous IT innovations interference to better understand the added value of infusing such AI innovations into their HRM processes. Moreover, when tackling the AI trust phenomenon, another very important factor to consider is the users' trust. This factor has shown to significantly control the rapidity of any IT innovations diffusion and success. Therefore, even if organizations and managers trust AI adoption in HRM, it is recommended to investigate users (e.g. employees, applicants) attitudes and levels of acceptance. For instance, would they prefer a human scanning their CVs or they trust an AI-based software to handle this task?

The research concluded that among the TOE factors firm size and TMS has a moderate effect on AI acceptance, thus not as much significant as trust and relative advantage factors. Moreover, contradicting the conventional perception of technological readiness significance in adopting IT innovations, hence, in terms of AI, machine learning and smart HR applications, technological readiness is not a significant determinant. Additionally, it was concluded that competitive pressure does not affect the attitude toward the adoption of AI in HRM at the current adoption phase. Consequently, at this early phase of adoption, the decision-makers and service providers should place a higher emphasis on AI applications features as a determinant of its success rather than on organizational or environmental factors which have less significance on AI diffusion. These conclusions answer the fifth research question.

Considering the expanding variation in terms of technology adoption between different industries, researchers are advised to consider the sectorial element for the potential adopter to better understand the influence of this variation and defined high adoption industries. The TOE factors significance in determining the AI adoption might differ if the industry factor is considered as a mediator for this relationship. For instance, competitive pressure may dramatically increase within high-tech industries. Further, based on these research findings, researchers are advised to place a higher emphasis on investigating the internal and external socio-cultural factors when investigating AI adoption in HRM than internal situational factors. The national cultural background is among these highly influential factors. For instance, the extent of individualism-collectivism, uncertainty avoidance, and power distance (strength of social hierarchy) have been shown a powerful influence in terms of IT innovations diffusion.

With regards to the extent of the significance of which HR roles have as a predictor of the Attitude toward AI in HRM, it is concluded that the emphasized HR roles within the organization and its strategic or employees focus have no relationship with HR leaders' attitude toward the adoption of AI in HRM. However, the association between the administrative role HRM and attitude toward adoption was not examined, therefore, the result about the absence of prediction effect of HR roles is not generalized and needs further investigation. These conclusions answer the sixth research question.

Additional to the emphasized roles of HRM, researchers are recommended to consider the preferred HR roles to gain an increased understating of this relationship. Moreover, at this early diffusion phase, it is valuable to provide insights into the impact of which AI applications have on changing the HR roles within the organization. While previously adopted IT innovations in HRM (HRIS, e-HR) have oriented HR into a strategic role, the effect of AI still unknown. Would it be a continuation of strategic enrichment? or just simply eliminates a specific task of which were considered before as essential HRM tasks without any significant change to the HRM functional roles within the organization.

While this research and other reports reflect a positive attitude toward utilizing AI in processing HRM tasks, thus when it comes to the actual use and adoption, reports showed a degree of reluctance as well. An additional recommendation is to investigate the relationship between the attitude toward AI adoption and behavioural intention and actual use. Therefore, researchers, policymakers and service providers are recommended to investigate this phenomenon from two perspectives, first to assess the attitude influence on actual adoption decision, second is to investigate the factors in which could affect this influence.

According to economic and academic indicators, AI technologies are expected to acquire a continuous increase in research, investments, and involvement within business processes in the upcoming future. This movement toward automation and AI autonomous intelligence poses a major change that reshapes economics, organizations, and business conduct. For HRM, to produce better and more effective results, a progressive reliance on augmented intelligence is expected where routine, administrative, and time-consuming tasks will gradually be replaced by smart AI technologies. These changes could constitute a competitive threat for laggard organizations in adopting such advancements. For instance, in the context of HR, this could mean hindering organizations capability to acquire, develop and retain qualified talents. Therefore, organizations and HR leaders are encouraged to remain updated with AI development research, follow up market adoption practices, and explore the potential influence on HRM functions.

7. MAIN CONCLUSIONS AND NOVEL FINDINGS OF THE dISSERTATION

This Research has tackled the phenomenon of adopting artificial intelligence applications in human resources management. Through developing a conceptual framework and analytical tools based on Rogers's Innovation Diffusion Theory (Rogers, 2003), TOE (Tornatzky et al., 1990), HR roles theory (Ulrich, 1997), and previous studies of IT adoption, this research findings provided empirical evidence about HR leaders' attitude toward the adoption of AI applications in HRM. The research findings reveal that leaders have a positive attitude and trust toward the potential contribution of emerging AI applications to support HRM efficiency, effectiveness, and quality. Moreover, findings showed a constructive perception about AI relative advantage which anticipates the continuation of future reliance on AI within HRM processes and supports the premise of augmented intelligence. This reliance deems a distinctive elevation of IT role within HRM and will significantly affect the HRM conduct and core competencies. Further, it was concluded that high predictive power is associated with innovation characteristics and technology trust factors, the low predictive power of TOE factors, and the absence of association of HR roles factor, with the attitude toward AI adoption in HRM. The traditional picture about the adoption factors strengths is changing and the prediction power is moving from situational, structural and TOE factors toward product features and trust.

The novelty of this research relies upon three levels, the research topic, design, and the findings of investigated factors. At the research topic level, while (Robinson, 2019) qualitative research studied HR practitioners attitudes and perspectives of AI technology in the hiring process, no previous quantitative research has been conducted to investigate the phenomenon of the adoption of AI applications in HRM.

From the research design perspective, the novelty is within the selected targeted research population. To gain more reliable and credible findings of the attitude toward the adoption of AI in HRM, this research population is confined to decision-makers and policymakers' level within the HRM hierarchy (specifically, CHRO, HR Directors, Senior HR managers, HR managers). Moreover, the novelty within the geographical element of the research population where no previous research has assessed AI adoption in HRM in the Middle East.

The Third level of novelty relies upon the research findings, no previous research has empirically investigated the association between innovation characteristics, technology trust, TOE factors, and the emphasized HR roles with attitude toward the adoption of AI in HRM. The following are the novel research findings of the research problem:

- In terms of innovation characteristics among the essential research novel findings are that the more perceived profitability (cost-saving) and fewer security concerns, the more perceived relative advantage of AI by HR leaders. Also, HR leaders' perception of AI applications relative advantage strongly influences their attitude toward its adoption. Additionally, the high perceived complexity by HR leaders negatively influences their attitude toward the adoption of AI applications in HRM. Lastly, HR leaders' perception of the level of normative compatibility of AI with the organization does not significantly influence their attitude toward it.
- From Technology trust perspective two main research novel findings, first is that HR leaders' perceptions of AI applications credibility, reliability and technical competence strongly influence their trust in such applications. The second is that their trust in AI applications is a significant positive predictor of their attitude toward its adoption.
- Another novel finding of this research is that TOE adoption determinants, namely firm size, top management support, technological readiness, and competitive pressure have no empirically significant influential relationship with HR leaders' attitude toward the adoption of AI in HRM.
- Another unique research finding is that the emphasized HR roles within the organization, specifically strategic partner, employee champion, and change agent, do not have a significant influence on HR leaders' attitude toward the adoption of AI in HRM.

While a comprehensive understanding of the research phenomenon needs a wide range of additional investigations in which covers other dimensions and factors, yet this research adds a valuable novel contribution to the theory during his early diffusion phase in which can be furtherly built on. This research contributes to the theory development of information technology diffusion in HRM. It expands the existing body of knowledge about organizational adoption of HRIS by providing an empirical finding of the emerging AI-based smart HRIS adoption.

SUMMARY

This research has tackled the phenomenon of AI diffusion within the HRM function. Specifically, assessing its determinants from HR leaders' perspective to provide a better understanding of the significant factors of which influences their attitude toward it. The declared general aim was to provide valuable inputs for organisations, policymakers, service providers, and researchers about AI adoption. These inputs are useful in preparing HR leaders and organizations for the technological changes associated with the increased reliance on AI, machine learning, connectivity, big data and other recent innovations. Moreover, a useful input for service providers in terms of the key factors that influence AI adoption and diffusion. Several reasons and motivations were behind choosing this research area among which my own seven years of professional experience in the HRM field in the Middle East region where I could observe the impact of emerging smart AI-based applications on the HR function. Also, my personnel curiosity and interest in predicting and understanding the future of management science with high AI involvement.

This dissertation consists of seven chapters of which covered the theoretical and analytical aspects of research and provided findings and conclusions. At first, the introduction addressed the research phenomenon by presenting a concise background about the research topic, highlighted the research problem and defined the gaps in which the research aims to fill. Chapter one has translated those gaps in research into a specific aim, objectives, and research question to be the ground base that guides the research further phases and helps in evaluating the research result. Besides, a concise description of the research methodology and hypothesises were provided.

The second chapter was dedicated to the technical literature review. It aimed to provide a comprehensive overview of the research topic and the previous literature contributions. Therefore, an interlocution bout the emergence of AI science, its research and distinctive impact was provided. Moreover, the historical development of IT diffusion within HRM, the literature of AI techniques in HRM functions, and outline some of the trendy used AI applications within the market and their potential impact on HRM quality. Also, this chapter has introduced several IT adoption models and previously investigated HRIS adoption research in which have directly contributed to this research.

The third chapter has introduced the research conceptual framework. The framework graphically illustrated the research constructs and the hypothesized relationships between the research variables. Moreover, defined the research variables, examine their appearance within previous literature and its prediction role in explaining the phenomenon of IT innovations adoption. The investigated factors were categorized into four constructs of innovation characteristics, technology trust, TOE, and HR roles. Lastly, based on the introduced framework the research hypothesises were fully presented and explained.

The fourth chapter provided a detailed description of the research materials and methods. At first, a general introduction into research methodology then introduces the applied paradigms and approach for this research. Further, the research designed was addressed by describing the research strategy, researcher interference, study setting, unit of analysis, time horizon, the data collection method, sample design, and tools of measurement. The research was conducted among HR leaders in the Middle East country, specifically, Jordan Kuwait Saudi Arabia and Qatar and the data were collected through an online questioner. A total of 389 valid responses were received and furtherly analyzed.

The Fifth chapter is data analysis and research findings. Several quantitative data analyses have been performed which involved data alteration, transforming and evaluation using SPSS 25 software to produce meaningful results that answer the research questions. At first, the sample demographics were introduced for a better understanding of sample characteristics. Further analyses were conducted to assess the validity and reliability of the research instrument; therefore, factor analysis was performed to examine the underlying structure of research variables items and alpha value to assess its reliability. Once validity and reliability were confirmed, the data appropriateness for regression analysis was examined through the measures of normality, multicollinearity and homoscedasticity and the appropriateness for regression analysis were confirmed. Consequently, the research hypotheses were tested through the use of multiple regression analysis and the results were presented. Lastly, to maintain a better understanding and conclusions, research findings were summarized and discussed in line with previously presented literature.

The sixth chapter presented the research interpreted the research findings into conclusions of which addressed the research objectives and provides answers for the research question. Also, the chapter provided researchers, organizations, policymakers, and HR leaders with recommendations about the interpretation of these research findings and further fields of interest. The last chapter (chapter 7) provided the main conclusions and novel findings of this dissertation.

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4. **Hmoud, B. I. F.**, Várallyai, L.: Artificial Intelligence in Human Resources Information Systems: Investigating its Trust and Adoption Determinants.
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5. **Hmoud, B. I. F.**, Várallyai, L.: Will Artificial Intelligence Take Over Humanresources Recruitment and Selection?
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