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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 investment 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-adopters' 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, the vast majority of 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 (G. 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?

1.4. RESEARCH METHODOLOGY

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. Therefore, This research 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 secondary data 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 is used to collect this research primary data from HR leaders in Middle East Countries, specifically: Jordan, Kuwait, Saudi Arabia, and Qatar. 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.

1.5. RESEARCH HYPOTHESES

To answer the research question the research has four main research hypotheses. The hypotheses reflect the four main research constructs with their underlying sub- hypotheses which are explained furtherly in Chapter 3 "Conceptual framework" and listed below:

1. **Innovation Characteristics: H1**. Innovation Characteristics has a significant influence on HR leaders' attitude toward the adoption of AI in HRM.
   - **H1.1:** Profitability has a significant positive influence on HR leaders' perception of AI Relative Advantage.
   - **H1.2:** Technical Concerns has a significant negative influence on HR leaders' perception of AI Relative Advantage.
   - **H1.3:** Relative Advantage has a significant positive influence on HR leaders' attitude toward the adoption of AI in HRM.
   - **H1.4:** Compatibility has a significant positive influence on HR leaders' attitude toward the adoption of AI in HRM.
   - **H1.5:** Complexity has a significant negative influence on HR leaders' attitude toward the adoption of AI in HRM.

2. **Technology-organization-Environment(TOE): H2**.Technology-Organization-Environment (TOE) factors have a significant influence on the HR leaders' attitude toward the adoption of AI in HRM.
   - **H2.1:** Top Management Support has a significant positive influence on the HR leaders' attitude toward the adoption of AI in HRM.
   - **H2.2:** Technological Readiness has no significant influence on the HR leaders' attitude toward the adoption of AI in HRM.
   - **H2.3:** Firm Size has a significant positive influence on the HR leaders' attitude toward the adoption of AI in HRM.
   - **H2.4:** Competitive Pressure has a significant positive influence on the HR leaders' attitude toward the adoption of AI in HRM.

3. **Technology Trust: H3.** Trust has a significant influence on the HR leaders' attitude toward the adoption of AI in HRM.
   - **H3.1:** Technical competence has a significant positive influence on HR leaders' trust in AI-HR solutions.
   - **H3.2** Reliability has a significant positive influence on HR leaders' trust in AI-HR solutions.
   - **H3.3** Credibility has a significant positive influence on HR leaders' trust in AI-HR solutions.

- **H3.4** Trust has a significant positive influence on the HR leaders' attitude toward the adoption of AI in HRM.

4. **HR-Roles: H4.** HR roles have a significant influence on the HR leaders' attitude toward the adoption of AI in HRM.
    - **H4.1:** Strategic Partner HR roles has a significant positive influence on the HR leaders' attitude toward the adoption of AI in HRM.
    - **H4.2:** Administrative Expert HR roles has a significant positive influence on the HR leaders' attitude toward the adoption of AI in HRM.
    - **H4.3:** Employee Champion HR roles has a significant negative influence on the HR leaders' attitude toward the adoption of AI in HRM.
    - **H4.4:** Change Agent HR roles has a significant positive influence on the HR leaders' attitude toward the adoption of AI in HRM.

2. TECHNICAL LITERATURE REVIEW

2.1. ARTIFICIAL INTELLIGENCE: THE REANIMATED SCIENCE

AI is claimed to be the backbone of industry 4.0 as well as future lifestyle. There is no doubt that the application of AI becomes widely more accepted than before, and its development is under the spotlight for many industries. Several reasons that granted AI increased importance among which, the imposed radical sweeping changes in businesses processes, profitability, and its impact on competitiveness. Despite that the argument about the benefits and threats of AI are escalating, the early debate about the degree of human reliance on AI has become less valid, rather, shifting the focus towards its applications. The term AI is not new it can be traced back to the mid of the twenty-century. The early conception of AI started to formulate when Warren McCulloch and Walter Pitts (1943) proposed a model of artificial neurons and the SNARC, the first neural network computer built by Marvin Minsky and Dean Edmonds in 1950. Thus, the most influential early AI work can be granted to Alan Turing and his paper “Computing Machinery and Intelligence” (Stuart J. & Peter, 2010). Turing presented the Turing Test linked to machine learning and genetic algorithms as an attempt to answer the question “Can machines think?”, he is considered the father of computer science (Lucci & Kopec, 2016). Even With Turing and other early contributions, the term Artificial Intelligence firstly introduced by John McCarthy (1956) during their two-month project at Dartmouth in the summer of 1956 where they announced “An attempt will be made to find how to make machines use language, form abstractions, and concepts, solve kinds of problems now reserved for humans, and improve themselves” and later suggests that AI become a separate field (Stuart J. & Peter, 2010).

Despite the early contributions which resulted from the development of expert systems, AI has been introduced as an industry, only after the 1980s. Early investments in the AI industry were oriented toward industrial robotics and the automation of complex, repetitive, and precise tasks. In the ninetieths, advance AI-based software’s have been developed such as IBM “Deep Blue” which have defeated the world chess champion Gary Kasparov, text prediction, and IBM Watson computer system which have won the popular quiz show “Jeopardy” (Yoav et al., 2017). The years after witnessed the emergence of the Data Mining concept and Intelligent Agents which represents a big step toward today's conception of AI (Stuart J. & Peter, 2010).

No doubt that these early applications and definitions of AI are considered outdated in today's perceptions about AI science and rather than regular computer software. The absence of supporting hardware and networks have held AI for years from demonstrating its true potential. Hence, resulted from the development of algorithms, network performance, and data storage capacity during the last decade, it can be asserted that a new era of AI has seen the light. Contemporary AI is defined as “create computer software and/or hardware systems that exhibit thinking comparable to that of humans,” (Lucci & Kopec, 2016). In other words, an intelligence that can imitate the human brain, recognize, examine, and interact, learn, and handle complex tasks in which usually associated with human intelligence autonomously without human intervention (Cam et al., 2019), Therefore, among the prevailing terms in AI today are machine learning and artificial neural network (ANN). Charlier & Kloppenburg, (2017) have defined three levels of intelligent digitalization, assisted Intelligence, augmented Intelligence, and autonomous intelligence. Assisted Intelligence which already widely available to automate repetitive, consistent, and time-consuming tasks such as manufacturing automation and GPS navigation programs that consider road conditions, and personalized advertisements. Augmented Intelligence is still emerging and considered a fundamental change where it brings man and machine to jointly make decisions and enable humans to perfume tasks cannot do otherwise (Charlier & Kloppenburg, 2017). Autonomous intelligence represents the most advanced form of technology in which be dependent on AI to act on its own at the subconscious level of information where algorithms autonomously take over decision-making and selection processes. Hence, ethics, privacy, data security, and control are major concerns at this level (Charlier & Kloppenburg, 2017).

2.1.1. AI in Research

Nowadays, AI has become more than just theories about machine ability to learn and autonomously process tasks, we can say that AI has penetrated almost every aspect of human lives. With more adopters reporting increased revenue in their companies and cost-saving (Cam et al., 2019), the AI role continues to grow and returns are tempting all industries to take its adoption more seriously. The reports indicate a growing gap between early adopters’ businesses and reluctant ones (Bughin et al., 2017). According to “Artificial Intelligence Index Report 2019” worldwide private AI investment has reached $70B in which $37B in AI-related startup investments with constant annual growth of 48%. Nowadays, a wide range of sectors are considering AI as a necessary element in their strategic planning process (Perrault et al., 2019). Further, 58% surveyed large companies indicated that AI- technologies are adopted in at least one business unit or function. For instance, besides advanced robotics usage in cars manufacturing, AI investment by autonomous cars companies has recorded the leading share of overall investment with $7.7B (9.9% of the total) in 2019 and it is expected that autonomous cars will consist 80% of cars production (Bughin et al., 2017; Perrault et al., 2019). Engineering, telecommunication, customer service, financial services, healthcare, pharma and medical production, and travel and tourism are among the highest AI-adopters' industries.

Academically, from less than 1% in the late 1990s, for the last two decades, AI papers have grown three-fold to record 3% of peer-reviewed journal publications and 9% of published conference papers (Perrault et al., 2019). Observing AI research, academic attention can be classified into three categories. First, its application and implementation kind of literature which concerned with exploring AI development, its application, and the potential advantages that AI technology can offer for a variety of disciplines. This AI research category is leading in terms of quantity and value, and it is considered more technical, where the research innovation-oriented and concerns more about discoveries related to AI science and applications. There is no discipline of research in which AI research skips, for instance, in healthcare (Choy et al., 2018; T. Sun & Medaglia, 2018; Ziuzianski et al., 2014), finance (Bahrammirzaee, 2010; D. Choi & Lee, 2018), education (Du Boulay, 2016; Popenici & Kerr, 2017; Roll & Wylie, 2016). The overall attitude of this category of literature has maintained its positivity towards AI advancement and perceived it as an opportunity to improve work tasks processes, quality, and results. While some scholars have played an advocate role in pushing AI adoption forward with no indecision, others maintained their positivity, however, with caution.

The second research category is economic (M. H. Huang & Rust, 2018). This literature category is directed toward understanding the impact of AI adoption on individuals, organizations, and economic systems-level and its adoption and diffusion factors (Grover et al., 2020; Ivanov & Webster, 2017; Puklavec et al., 2018; Tanwar et al., 2020). While the first category literature is considered to have a positive attitude towards AI-based innovations, the second category literature is more neutral toward AI, aiming to provide valid examination about its actual or predicted influence, for instance on jobs and functions (Agrawal et al., 2019; Greenman, 2017; M. H. Huang & Rust, 2018; Levy, 2018), long-term and short-term economic systems (Xueming Luo et al., 2019; Milgrom & Tadelis, 2018), and society (Hwang, 2018; Makridakis, 2017; Nadikattu, 2016). Huang & Rust (2018) addressed the AI threat on jobs and developed a four dimensions AI job replacement theory. They have defined four levels of intelligence that organizations may incorporate on task level through AI technologies (see

Figure 1), mechanical, analytical, intuitive, and empathetic (M. H. Huang & Rust, 2018). They argued that organizations should choose between humans or AI in completing specific tasks based on these four levels of intelligence. Mechanical intelligence is considered the basic level in which was adopted during the early stage of AI diffusion, is related to the automation of repetitive tasks such as manufacturing robotics. While analytical intelligence is concerns with problem-solving and machine learning through logical reasoning and mathematical skills, an example of this intelligence is (IBM) chess software Deep Blue (M. H. Huang & Rust, 2018).

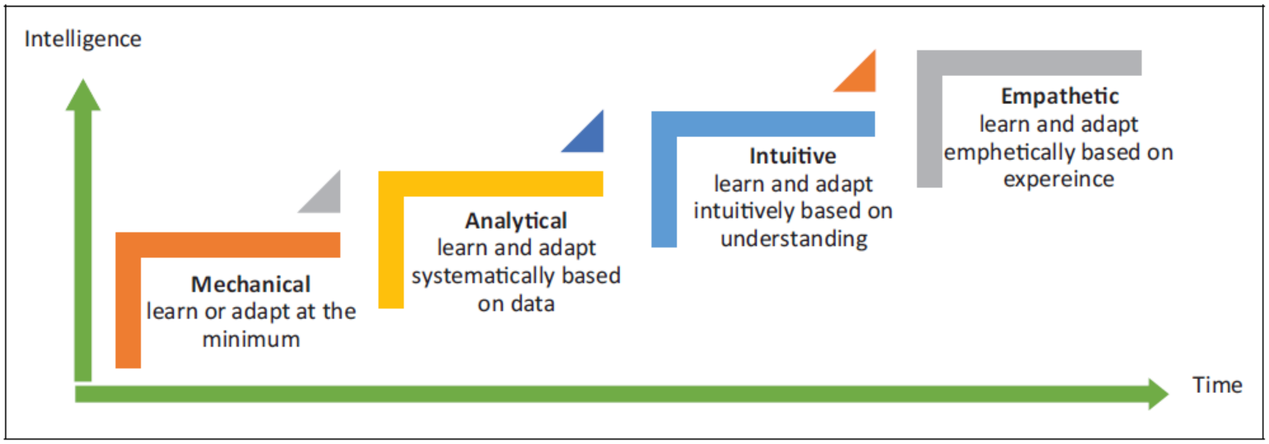

Figure 1: Levels of Intelligence
Source: (M. H. Huang & Rust, 2018)

Intuitive intelligence is associated with experienced-based thinking in which includes creativity and understanding. some examples of intuitive intelligence are IBM Jeopardy, Google's DeepMind AlphaGo, and AI poker player "Libratus" (M. H. Huang & Rust, 2018). The development of Intuitive intelligence was much connected with the invention of speech and vision recognition and the ability to access huge bulk of data while understanding its content. These AI-based programs demonstrated the ability to learn intuitively simulates human instinct in the decision-making process. Intuitive intelligence is considered the current viral aspect of AI that has the major competition and potential to add a significant value to a variety of tasks such as autonomous cars, medical surgery, and financial service (Brynjolfsson & Mitchell, 2017). Empathetic Intelligence is AI's ability to understand human emotions and interact emotionally as well-argued to be the future and the most advanced version of AI application. The level of intelligence is a cause of debate among scientists, while psychologist defines emotions as a biological reaction, AI experts believe that it is cognitive and can be programmed (Brynjolfsson & Mitchell, 2017; M. H. Huang & Rust, 2018; Perrault et al., 2019). Whether it is human or computational emotion, AI is demonstrating a major potential contribution in tasks that require to communicate emotionally. Empathetic intelligence applications are still limited such as Sophia, the human-like AI from Hanson Robotics, and “Replika” the online personal artificial intelligence friend (M. H. Huang & Rust, 2018).

The third AI-research category is the research in which directed toward understanding the ethical and functional implications, and associated risks with AI application. Generally, the literature of this category maintains a conservative attitude toward AI application. Trust, algorithmic biases, losing jobs, virtual threats and cybersecurity, social impact, and process ambiguity are some of the viral topics of this category and claimed AI implications. (Guan, 2019; T. C. W. Lin, 2019).

2.1.2. Distinctive Advantages of AI

The most common argument that reluctant adopters use is if AI is meant to operate tasks that else require human intelligence, why would we replace humans with machines and losing more jobs? While the question seems simple, however, the answer is not. AI is argued to provide undeniable values, economic evolutions, and change the way how the business operates. This section will highlight some of the benefits that AI offers from two perspectives. First is efficiency, while the early information systems have had a major contribution in transferring tasks processing from direct and paper-based into a computerized process in which improved quality, saved time, and lowered the cost, however, these systems need human intervention to process. AI is capable to mimic human intelligence in making decisions and deliver results without human interventions either fully autonomous intelligence or limited augmented intelligence (Lucci & Kopec, 2016). Chui et al., (2015) argued that when studying automation, the focus should be on certain activities rather than an entire occupation, hence, their research suggests that current AI technologies are capable to automate 45 per cent of activities within the USA businesses including highly paid senior executives’ jobs. Further, on an occupational level, current technologies can automate fewer than 5 per cent of occupations, however, 60 per cent of them consists of 30 per cent or more activities that could be automated (Chui et al., 2015). AI technologies increase operational efficiency by several means among which, substantially save cost, process a large scale of complex tasks much faster than conventional methods have significantly boosted productivity, swifter decision-making process, and eliminate human error, deficiencies, and bias. The second aspect is quality. in terms of quality, AI has drastically raised the standard of conducting businesses in many aspects among which, instantaneous real-time customer-assistance services wgich increased customer satisfaction. Moreover, machine learning has enabled companies to predict customer preferences, evaluate and learn customers experience, and personalize marketing process and the consistent availability of services has increased customer engagement (Davenport & Ronanki, 2018).

2.2. IT DIFFUSION IN HRM

The information technology diffusion in HRM can be classified into three eras: HRIS, E-HR, Smart HR

2.2.1. First Era: HRIS

The first era started with computers and information technology emergence, which traced back to the 70s. During this era, the concept of HRIS has evolved and gained wide attention across researchers and scholars. Early scholars have defined HRIS as information systems that acquire, store, maintain, analyze, retrieve, distribute, and validating data about organization human resources (DeSanctis, 1986; Hendrickson, 2003; Kovach & Cathcart, 1999). In other words, it was the process of computerizing HRM by electronically managing employees' records, transaction processing, and the integration of HRM processes. At first, when computer operating systems were at a simple data-entry level, the focus was directed toward accounting and finance processing, similarly, personnel units were first in utilizing IT mainly to handle basic employees financial-related processes and record-keeping such as payroll, tax, and benefits (Kovach & Cathcart, 1999). Among the early factors that provoked HRIS adoption is the governmental employment and tax policies, statistics by the end-70s statistics have shown that 40% of companies have in-house personnel management systems (DeSanctis, 1986). Probably at that phase employee data were stored in flat-file format and retrieved through keyword or unique employee identifier (Ball, 2001). Despite this early reliance on HRIS at the personnel department level, researchers believed that HRM lagged other organization functions in utilizing IT (Tansley et al., 2001; Tansley & Watson, 2000). Among the early impact that this early application had is timesaving when performing administrative tasks, downsize personnel staff, reduce paperwork, and improved accuracy.

However, by the beginning of the twenty-first century, the development of IT capabilities and declining costs have endorsed its utilization in more sophisticated functions of HRM. At that point, the majority of corporations have recognized HRIS as an integral system and furnished managerial and technical needed support to its operation. Apart from technical development, increased utilization of HRIS was associated with the elevated HRM role within organizations. Further, globalization, complexity, diversity, changing organizational structure, rapidly changing policies, and the increased need for HR reports and supports, have strategically strengthened the importance of HRM in general and HRIS in specific (Ball, 2001; Tansley & Watson, 2000). Consequently, these factors promoted HRIS as a strategic decision support system and enriched utilization in more HRM functions such as manpower planning, human capital management, and HR forecasting and analysis (Hendrickson, 2003).

Since its emergence, HRIS has drawn research attention from different perspectives. For instance, assessing its implementation nationally (Ball, 2001; C. Y. Y. Lin, 1997; Ngai & Wat, 2004; T. Teo et al., 2007) or on a specific sector (Troshani et al., 2011), understanding its impact on the organization, such as its impact on HR functionality (Khera, 2012; Kovach et al., 2002; Maier et al., 2013; B. Y. Obeidat, 2012; Wiblen et al., 2010), or organization efficiency (Al-Tarawneh & Tarawneh, 2012; Kaygusuz et al., 2016; Khashman & Khashman, 2016). Another research perspective was concerned with exploring the internal and external factors that affect its successful implementation and adoption (Ahmer, 2013; Rand H. Al-Dmour & Al-Zu'bi, 2014; Haines & Petit, 1997; T. Teo et al., 2007; Urbano & Yordanova, 2008).

2.2.2. Second Era: E-HR

The second era is claimed to be started in the early 90s with the internet invention, however, its lineaments started to be brighter later after the spread of internet service and the emergence of E-commerce and E-business. From an HRIS perspective, HR departments were not immune from such emerging trends, and so, this era has witnessed the birth of e-HR (Bondarouk et al., 2009). Despite the explicit variance when it comes to the term, some of the widely used terms such as Virtual HR (Lepak & Snell, 1998), web-based HR (Ruël et al., 2004), and intranet-based HRM, all refer to the same phenomenon (Strohmeier, 2007). While Scholars (Lengnick-Hall & Moritz, 2003; Ruël et al., 2004; Voermans & Van Veldhoven, 2007) synopsis e-HR definition by emphasizing the role of internet in conducting HR services and policies, Ruël et al., (2004) define e-HRM as “a way of implementing HRM strategies, policies, and practices in organizations through the conscious and direct support of and/or with the full use of channels based on web-technologies”, Strohmeier (2007) defines e-HR as " the (planning, implementation and) application of information technology for both networking and supporting at least two individual or collective actors in their shared performing of HR activities.". In other words, e-HR is transforming HRIS into a virtual online service that is accessible at any time and connects all stakeholders simultaneously. Strohmeier's definition highlighted the role of e-HR in creating an interactive medium that connects and integrates spatial actors regardless of their geographical disengagement. It also emphasizes its role in enhancing task fulfilment by supporting or substitutes conventional methods (Strohmeier, 2007).

While HRIS meant to enhance internal HR processes and were exclusively oriented to be used by HR personnel within organizations, e-HR expanded this cycle and integrated various users and stakeholders. E-HR involved targeted groups from the outside of the HR department and across organizational boundaries, in a way that enabled managers and employees to become more of partners with HRM by getting involved in activities that once were considered exclusively among the HR administration and personnel domain (Lengnick-Hall & Moritz, 2003; Ruël et al., 2004). This thought an outbreak of conventional HRM and as any other major change, some have perceived it as an opportunity while others considered it as a threat. Although HRIS reduced the burden of administrative tasks, e-HR has opened new doors toward an increased HR alignment within the organization (Bondarouk et al., 2017; Gardner et al., 2003). E-HR had a major role in the process of transforming the HR function advantageously and strategically within organizations by promoting employees and external stakeholder engagement. Thus, it sparked an insight regarding the extent of continuously evolving HR roles in response to technological advancement. As a result, new theories, and an updated vision of HR roles within organizations started to emerge. The new emphasis aimed to explain their role as change agents and strategic partner (Ulrich, 1998). Promoting HR's vital role in knowledge sharing and strategic analysis (Troshani et al., 2011).

E-HR diffusion has been subject to several factors that varied in their significance and context. Among the important factors that played a significant early role is the competitive pressure. The emergence of e-business has put more pressure on organizations to be strategic, flexible in terms of decision-making and practices, efficient (e.g. cost), and customer service oriented (Ruël et al., 2004). Big companies were able to achieve these objectives at the HRM level by incorporating e-HR, especially with talent acquisition and communication. Moreover, Ruël et al., (2004) highlighted the social factor where the increased labour supply shortage, individualization, education, and access to new markets have shifted the power of the employment relationship in favour of employees, hence e-HR facilitated the accommodation of such social change. Further, the overall strategic direction of the organization is another factor that affected e-HR utilization (Marler & Parry, 2013; Oliveira & Martins, 2010), in other words, organization perception toward the HR department has diverged between emphasizing or neglecting HRM strategic role. Organizations in which desired an increased strategic involvement of the HR department have adopted e-HR to fulfil their strategic goals more instantly than other organizations (Marler & Parry, 2013).

Despite the noticeable lag in fully conceiving and actualizing such changes, especially in SMEs, yet nowadays e-HR has become a crucial component and tool in HR systems configuration, and no doubt that researchers and practitioners agree that e-HR is inevitable. Recruitment, for instance, took the lead for going online with emerged "e-recruitments". Applicants had the opportunity to explore vacancies, access job specifications, and apply instantly. Gradually, other HR functions implemented e-HR and no doubt that e-HR has had the most powerful impact on HRM. Granting access to a huge talent pool instantly, conducting online training, HR self-services systems, telecommuting, international HRM, and many other potentials that e-HR offered to the industry.

2.2.3. Third Era: Smart HR 4.0

While HRIS primary users were HR personnel and it had a major role in digitalizing the HRM, and e-HR have had a significant contribution in promoting HRM management strategically and virtually crossing the organizational boundaries, the third era of IT diffusion in HRM reflects the fourth industrial revolution (industry 4.0). There is no doubt that industry 4.0 is introducing major changes at both macroeconomics and microeconomics levels. Therefore, due to this rapid radical transformation in business processes, jobs, and service systems, Nowadays, the term Industry 4.0 has the spotlight and it is considered the most trendy area of research within the economical and technologic field of research (Ustundag & Emre, 2018). The Industry 4.0 concept has formally introduced in Germany in 2011 to represent the new strategic direction toward smart integration of all technological, human, and physical aspects of production within the organization (Hozdić, 2015; Roblek et al., 2016). Achieving this integration is dependent on combining numerous components through the utilization of AI, cloud computing, machine learning, augmented reality, Internet of Things (IoT), human-machine communication (C2M), and machines to machine communication (M2M) (Roblek et al., 2016; Ustundag & Emre, 2018). From an HRM perspective, industry 4.0 manifested by several means among which the emergence of AI-based solutions and machine learning in HR and have altered the methods of managing HR within organizations. While it is still considered at the early diffusion phase, nowadays, HR smart applications have gained more attention within industries and HR leadership. The source of this attention is the potential value-added in terms of automating time-consuming administrative tasks, improve efficacy, HR service quality, reduce cost, HR branding, customer satisfaction, and improve competitiveness. Reviewing the related literature, the heterogonous terms and the lack of a universal agreement over the used term used of which describes AI-based HR systems. For instance, Smart Human Resources 4.0 (Shamim et al., 2016; Sivathanu & Pillai, 2018), Human Resources Management 4.0 (Liboni et al., 2019), Intelligent information processing in human resource management (L. Zhang & Hong, 2006), and Intelligent Human Resource Information System (i-HRIS) (Masum et al., 2018). However, this research will refer to this phenomenon as AI in HRM. The next sections will provide an elaborated explanation about the emerging role of AI in HRM.

2.3. AI TECHNIQUES IN HRIS LITERATURE

Tracing the literature, it is noticeable that it 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 other AI techniques (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 prospected solutions to improve the hiring process efficiency and job matching. However, researchers have also explored AI applications in several other HR functionalities, the following are some of AI literature that offers a heterogeneous set of research concerning how certain AI techniques could be utilized for specific HR domain.

2.3.1. Talent Acquisition

Talent Acquisition (also referred to as recruiting, staffing, and hiring) is the HRM function that "involves actions and activities taken by an organization to identify and attract individuals to the organization who have the capabilities to help the organization realize its strategic objectives" (Arne et al., 2006). The recruiting process composes of planning, sourcing the candidate, pre-assessment, final selection, job offer, and contracting. Among the earliest AI tool in which utilized in the employee sourcing process is a knowledge-based search engine (Strohmeier & Franca, 2015). This tool was integrated with the web-based talents sourcing platforms and designed to best match contents.

employers define a keyword or a “reasoner” which best describes the job features such as job title, skills, and qualifications, based on the semantic annotation of defined characteristics, knowledge-based search engines extract the matching candidates (Mochol et al., 2007). Hence, to improve the search result it uses a predefined ontology-driven knowledge extraction (Çelik, 2016). For instance, the search engine would recognize that “sales director semantically corresponds with a searched position marketing manager among others” (Strohmeier & Franca, 2015). Moreover, studies (Daramola et al., 2010; Mehrabad & Brojeny, 2007) have introduced expert systems models to improve human resources recruitment and selection effectiveness. While (Dursun & Karsak, 2010; Golec & Kahya, 2007; Kabak et al., 2012; H. T. Lin, 2010) have applied fuzzy tools in the human resources selection process.

To process this huge amount of data, data mining tasks of classification, clustering, regression, summarization, dependency modelling, and deviation detection (Kantardzic, 2020; Sumathi & Sivanandam, 2006) have been recognized in improving HR recruitment and selection. For instance, Chien & Chen, (2008) conducted an empirical study at a semiconductor company to support the hiring decision of engineers and managers in various job functions. They proposed a data mining framework to classify and predict applicant’s future performance and retention throughout the screening process based on demographics characteristics such as age, gender, education, and experience. Chien & Chen, (2007) tested an intelligent data mining system based on rough set theory with 29 identified rules to support high-potential talents retention. The proposed framework predicts job behaviour such as performance and resignation probability to alter the selection process and reduce fault employment.

Besides, scholars (Dursun & Karsak, 2010; Strohmeier & Franca, 2015) have perceived information extraction based on data mining as an effective tool in data acquisition during the applicants' screening process. For instance, Strohmeier & Franca (2015) have proposed an intelligent text mining technical model to assess applicants based on their sentiments within a textual context, the model applies sentiment analysis to analyzes unstructured text within the database to extracts sentiments and opinions by classifying them into “positive sentiments” and “negative sentiments”. L. F. Chen & Chien, (2011) introduced a model to identify high-potential talents who fit the company culture and job functional nature. Moreover, other studies (Dursun & Karsak, 2010; M. J. Huang et al., 2006; Sivaram & Ramar, 2010; Tai & Hsu, 2006) have tackled the phenomenon of subjective human judgment during recruitment and selection and proposed intelligent solutions that apply fuzzy data mining systems to support decision-making throughout the screening and process selection.

Another advanced AI tool in which caught HR selection research attention is Artificial Neural Network (ANN) and machine learning. The neural network is defined as “software systems that attempt to model the human nervous system, artificial neurons are connected with links in some prescribed topology” (Lucci & Kopec, 2016). ANN is much associated with reasoning and artificial learning capabilities and intends to capture the analogous structure of the human nervous system to simulate human learning ability (Lucci & Kopec, 2016). L. C. Huang et al., (2004) have integrated a neural network learning system into HRIS to deliver an AI-based scoring system for candidates who applied for managerial jobs opening. Boz & Kose, (2018) have introduced an ANN-based system that able to extract and interpret emotions from individuals’ facial expressions during an interview. Additionally, (Chang, 2010; Dwivedi et al., 2019; M. J. Huang et al., 2006; Thissen-roe, 2005; Tung et al., 2005) introduced a fuzzy ANN model that aims to discover implicit knowledge, predicted employee future performance, and then allocate proper persons for appropriate positions and projects. Also, (Hsu et al., 2019; Mahmoud et al., 2019) have applied a machine learning technique predicting applicants' future performance to support the hiring process, by utilizing performance management and social screening.

2.3.2. Turnover Prediction

Employee turnover can be defined as the percentage of the employee who leaves the organization voluntarily from the overall HR count. A turnover analysis is essential for organizations for several reasons, among which, provides data for use in the manpower planning process, investigate turbulence within the organization, improve retention strategies, take action for retention, succession planning and detect environmental threats such as increased competition (Armstrong, 2006). The turnover analysis was among the early phenomenon in which IT has played important role in helping the organization to analyze and predict. Consequently, AI research in HR has also explored the possible contribution of AI-based techniques in predicting employee turnover. For instance, (Nagadevara & Srinivasan, 2007) have applied various data mining techniques to predict turnover in the organization by analyzing the demographics and the employees' withdrawal behaviours. Moreover, literature has introduced other AI techniques for predicting employee turnover among which ANN-based models, (Ali Shah et al., 2020; Sexton et al., 2005; Soni et al., 2019; Strohmeier & Franca, 2015) and machine learning (Punnoose & Ajit, 2016; H. Zhang et al., 2018; Y. Zhao et al., 2018).

2.3.3. Human Resources Development (HRD)

Human resources development is one of the essential roles of HRM. HRD is related to managing HR learning, development, and training processes to improve individual, team, and organizational performance (Armstrong, 2006). HRD starts at the strategic level from defining the vision and goals and to the operation level of implementing activities to attain these organizational goals. Along with the emergence of HRIS and e-HR, HR training methods witnessed changes within their fundamental approach such as the face-to-face method. E-learning has transformed the HRD within the organization via several means, among which, collaborative e-learning, self-paced e-learning, and learning portals (Armstrong, 2006). However, the era of connectivity, cloud computing, and AI-based applications have redefined organizational learning through the emergence of contemporary Smart learning techniques. For instance, intelligent tutoring systems, log file, and clickstream analyses to predict learner success, virtual reality-based learning systems, games and simulations, capture learner's semantics through text mining, natural language voice recognition, peer assessments (Cope et al., 2020), smart video learning analytics (Giannakos et al., 2016), match training materials with employees learning aptitudes, records and occupations via data mining and expert system (K. K. Chen et al., 2007), AI-based training determinants analysis (Buzko et al., 2016), assessment agents for e-learning environments, extract efficient information from learners input through a genetic algorithm (Giotopoulos et al., 2006), employee self-service with interactive voice response (Strohmeier & Franca, 2015).

2.3.4. Performance Management

Performance management is defined as "a systematic process for improving organizational performance by developing the performance of individuals and teams" (Armstrong, 2006). It is considered the ground base for HRD and It is concerned with measuring and altering individual and group performance to attain the planned organizational objectives. Similar to other HR functions, IT has played an important role in PM processes within the organization. However, from an AI perspective, researchers have employed AI-based techniques to improve the PM process, for example, data mining to examine employees performance (Jing, 2009; Rashid & Jabar, 2016; X. Zhao, 2008), identify employees core competencies (Y. T. Lee, 2010; W. W. Wu, 2009), define organization competence ontologies (Ziebarth et al., 2009). Moreover, through Artificial Neural Networks (ANN) to evaluate workforce productivity and effectiveness (Azadeh & Zarrin, 2016). Further, other literature has tackled strategic HR management such as career planning (Lockamy & Service, 2011), and human capital planning (Li & China, 2009), while some have introduced a holistic AI-based decision support framework (Jantan et al., 2008; Masum et al., 2018). Table 1. summarizes the literature on AI techniques in HR based on the HRM domain.

From the literature, it is observable that scholars have perceived AI-based techniques as an opportunity to improve overall HRM services quality, however, the early focus on talent acquisition strategies and processes is visible. This focus can be justified by the importance of talent acquisition among other HR functions, the increased competitiveness on talents, and the intensity of hiring process tasks especially on the administrative level (Ployhart, 2006). AI tools have appreciably tackled the time-consuming tasks phenomenon through its contribution to lower the burden of sourcing, screening, and matching tasks through automation. Besides the technical impact, literature has also highlighted the impact on quality. For instance, human subjective judgment and bias during screening, assessment and selection process, instantaneous processing, and customer satisfaction were among the key tasks that AI tools plea to improve.

Table 1. Summary of AI Techniques in HR literature

HRM Domain	Task Domain	AI Techniques and literature
HR Sourcing	Match jobs with job seekers.	Knowledge-based search engines (Mochol et al., 2007; Strohmeier & Franca, 2015)
	Extract the matching candidates, Resumes information extraction.	Information Extraction (Çelik, 2016)
Applicants Evaluation, Selection and Allocation	Assessment of job applicants.	Data Mining (Dursun & Karsak, 2010; Strohmeier & Franca, 2015).
	Classify applicants.	Fuzzy Logic (Dursun & Karsak, 2010; Golec & Kahya, 2007; Kabak et al., 2012; H. T. Lin, 2010).
	Filter fitted candidates from a large volume of the applicant pool.	Fuzzy Data Mining (L. F. Chen & Chien, 2011; Dursun & Karsak, 2010; M. J. Huang et al., 2006; Sivaram & Ramar, 2010; Tai & Hsu, 2006).
	Predict future performance. Discover implicit knowledge.	Expert System (Daramola et al., 2010; Mehrabad & Brojeny, 2007).
	Human resources allocation to proper positions and projects.	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	Data Mining (Nagadevara & Srinivasan, 2007).
	Withdrawal behaviours	ANN (Ali Shah et al., 2020; Sexton et al., 2005; Soni et al., 2019; Strohmeier & Franca, 2015)

	Predict absenteeism Social scanning	Machine Learning (Punnoose & Ajit, 2016; H. 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 (Y. T. Lee, 2010; W. W. Wu, 2009). ANN (Azadeh & Zarrin, 2016).

Source: Author's Construction

While some of these proposed AI-solutions within the early literature were implemented, its implementation manifested as customized organizational level tools that were integrated into HRIS and e-HR to produce a better result. It did not provide a comprehensive functional-level solution in the same way as what HRIS and E-HR had. This can be explained by the same phenomenon in which caused AI science to lag behind the theory. Hardware and connectivity advancement have lagged the software, the theory precedes the application. For that reason, it took the hypothetical research a decade later to manifest as an industry that offers comprehensive outsourcing AI-based solutions for HR functions. Nowadays, intelligent talent acquisition solutions, Chatbots, AI-based analytical systems, virtual reality-based learning systems, and professional networking are growing and advancing rapidly.

2.4. TRENDING AI APPLICATIONS IN HRM AND EMERGENT THEMES

While it is considered the first step to make, it is argued that the success of the recruitment process is heavily linked to talent sourcing process effectiveness (Armstrong, 2006). Consequently, the wrongly decided sourcing method means severe consequences in terms of cost and time. Therefore, it is noticeable that the sourcing function is among the first HR functions 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 managers, 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 candidates, 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 are 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 are 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 expedite 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 in 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, Chatbots consistently provides instantaneous contact with applicants and neutralize human judgmental errors and biases. Chatbots offer comprehensive hiring services which 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). 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 & Varallyai, 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 which incorporates Industrial-Organizational Psychology and assess the candidates compared to the client's top performers (Tambe et al., 2018). Furthermore, 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).

2.4.1. 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 shortened the time needed for hire which enhanced the organisation's ability to fill skills gaps and vacancies faster. From a cost-wise perspective, 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. 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 HRM quality and organization branding. For instance, guarantee a fair, accurate, unbiased, and inclusive decision-making process. Besides, studies have shown that lack of communication and feedback is among the major factors that cause applicants' and HR negative perceptions about the organization, while on the other side, instant services are greatly connected with customer satisfaction (Adam et al., 2020), therefore, customer experience such as job applicants is a vital aspect of evaluating HRM quality. 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.

2.5. IT INNOVATIONS ADOPTION THEORIES

Along with early IT innovations diffusion, the study of its adoption and acceptance factors have been a prominent research area. That rapid changes at the firm and economic level have raised the importance of understanding these factors. Besides, understanding user acceptance and attitude toward any emerging technology have been viewed as a crucial element for its development (Taherdoost, 2018). In other words, realizing the factors that influence user decision to accept technology is an important input for designers and it is tightly integrated with the technology development process. Previously, innovation diffusion theory and application have helped to investigate and explicate the adoption and diffusion of several emerging IT innovations that are considered widely used in current days such as decision support systems, telecommunications and internet services (C. Kim & Galliers, 2004). Researchers have sought to investigate, predict, and explain these factors at the individual, organization, and environmental levels (Tarhini et al., 2015).

This literature review will present several adoption theories, yet, amongst the several established theories, the focus in this review is oriented toward the theories with association with the study context. Among which, the Technology Acceptance Model (TAM) (Davis 1986), Diffusion of Innovation (DOI) theory (Rogers, 2003), the Technology, Organization, and Environment (TOE) framework (Tornatzky and Fleischer 1990), The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al. 2003).

2.5.1. Technology Acceptance Model (TAM)

TAM was originally developed by (Davis, 1989) as an extension of the Theory of Reasoned Action (TRA) and It is considered the most widely used model to assess technology acceptance and adoption at the individual user level (Sohn & Kwon, 2020). While TRA argued that individual behavioural intention is a result of his beliefs and subjective norms, TAM emphasized the beliefs factor and eliminates the social influence on user attitude and actual use of IT innovation. Davis, (1989) emphasized that user motivation is driven by Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) as the two essential individual beliefs which directly associated with his attitude toward the information system (ATT), hence, his Behavioral Intention (BI) to accept (Fathema et al., 2015). Davis defined PEOU as "the degree to which a person believes that using a particular system would enhance his or her job performance" while PU is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989). According to TAM, Behavioral Intention (BI) is directly influenced by PU and ATT. This means if an individual perceives the introduced technology as noticeably useful to his job process, he will develop a positive attitude toward it as well as behavioural motivation to use it. Consequently, Behavioral Intention (BI) is directly associated with the actual adoption behaviour.

Throughout its experimental study, TAM underwent several development phases that led to some adjustments within its constructs. Among these, the noticeable direct association between PU and PEOU with BI has led to excluding the ATT construct as a mediator. Besides, The final version of TAM has excluded included external variables which have a potential impact on BI via the mediation of PEOU and PU (Lai, 2017; Tarhini et al., 2015). The fact that TAM considered the most widely applied model in technology acceptance studies enabled the deduction of its limitation (Tarhini et al., 2015). Among the addressed limitation of TAM is that it failed to explain the given results (Tarhini et al., 2015), disregards the social and cultural influence on technology acceptance (Bagozzi, 2007; Taherdoost, 2018; Tarhini et al., 2015), the overreliance and oversimplified conceptions of personal perception and emotions as a base for decision making, and finally the over-reliance solely on deterministic perspective without considering of "self-regulation processes" (Bagozzi, 2007).

Intending to overcome the shortcoming of TAM, Venkatesh and Davis (2000) proposed a modified version of TAM. TAM2 adds that it considered two new external factors that have a direct influence on predicting PU in which were ignored with the original model. The first factor is the social influence construct exemplified by image and subjective norm, the second factor is the cognitive construct exemplified by job relevance, output quality, and result demonstrability (Lai, 2017; Taherdoost, 2018). Later on (Venkatesh & Bala, 2008) integrated the TAM2 model with perceived ease of use (Venkatesh, 2000) to present TAM3 (see Figure 2). TAM3 has included the earlier suggested determinants of PEOU and suggested the experience as a mediator between PEOU and PU, computer anxiety and PEOU, and PEOU and BI (Venkatesh & Bala, 2008).

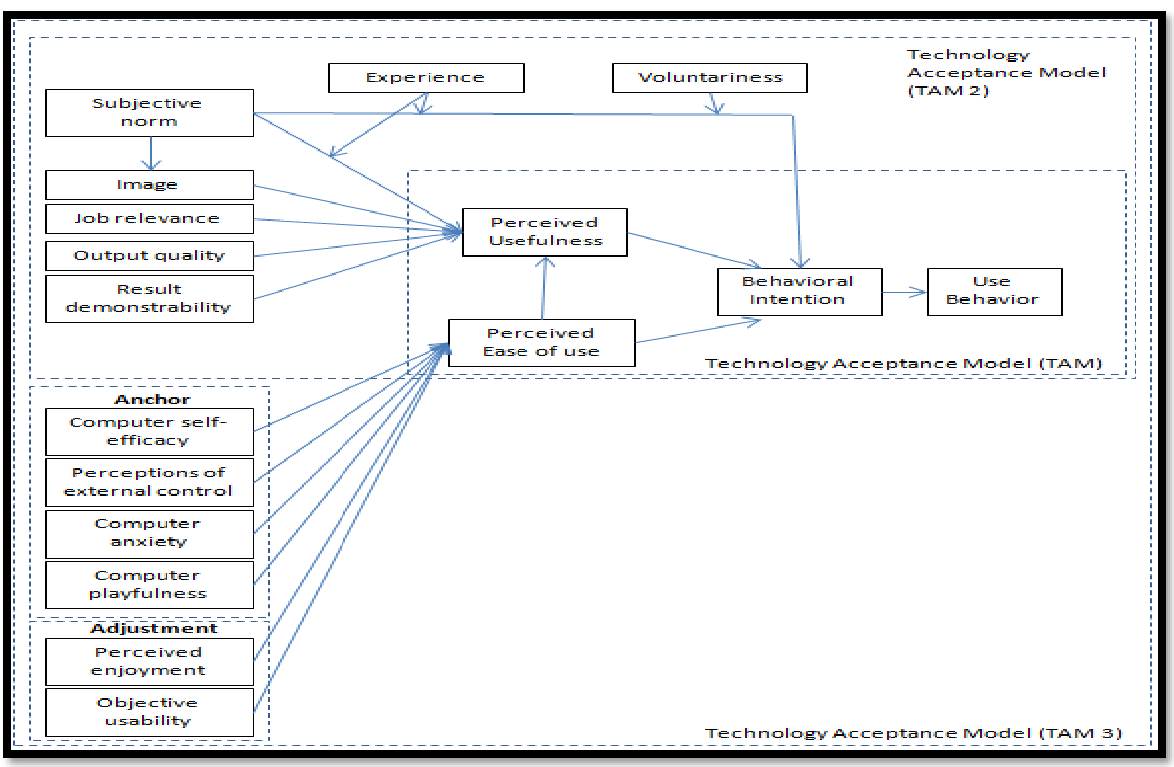

Figure 2: TAM3 Source: (Venkatesh & Bala, 2008)

2.5.2. Diffusion of Innovation (DOI) Theory

DOI theory by (Rogers, 2003) is a widely recognized theory that attempted to explain the phenomenon of accepting innovations and it was extensively used in IT innovations diffusion research. The theory suggests that innovation is a sequential process by which communicated through particular channels and specific time within a certain social system (Dearing & Cox, 2018; A. Lin & Chen, 2012). The theory suggests that the innovation diffusion process consists of five steps, knowledge of innovation, persuasion, decision, implementation, and confirmation (Tarhini et al., 2015). Further, Rogers, (2003) argued that individual and organizational perception of an innovation attributes is an essential predictor of its acceptance, thus, he specified five innovation attributes (see Figure 3), relative advantage, compatibility, complexity, observability, and trialability as an effectual predictors factors. However, DOI has received a critic about its poor applicability in specific industries and research contexts where the prediction attributes failed associate with innovation acceptance (Dearing & Cox, 2018). Other limitations are that it failed to explain the relationship between certain attitudes and adoption decisions, moreover, the relationship between the innovation attributes and expected attitude (Tarhini et al., 2015).

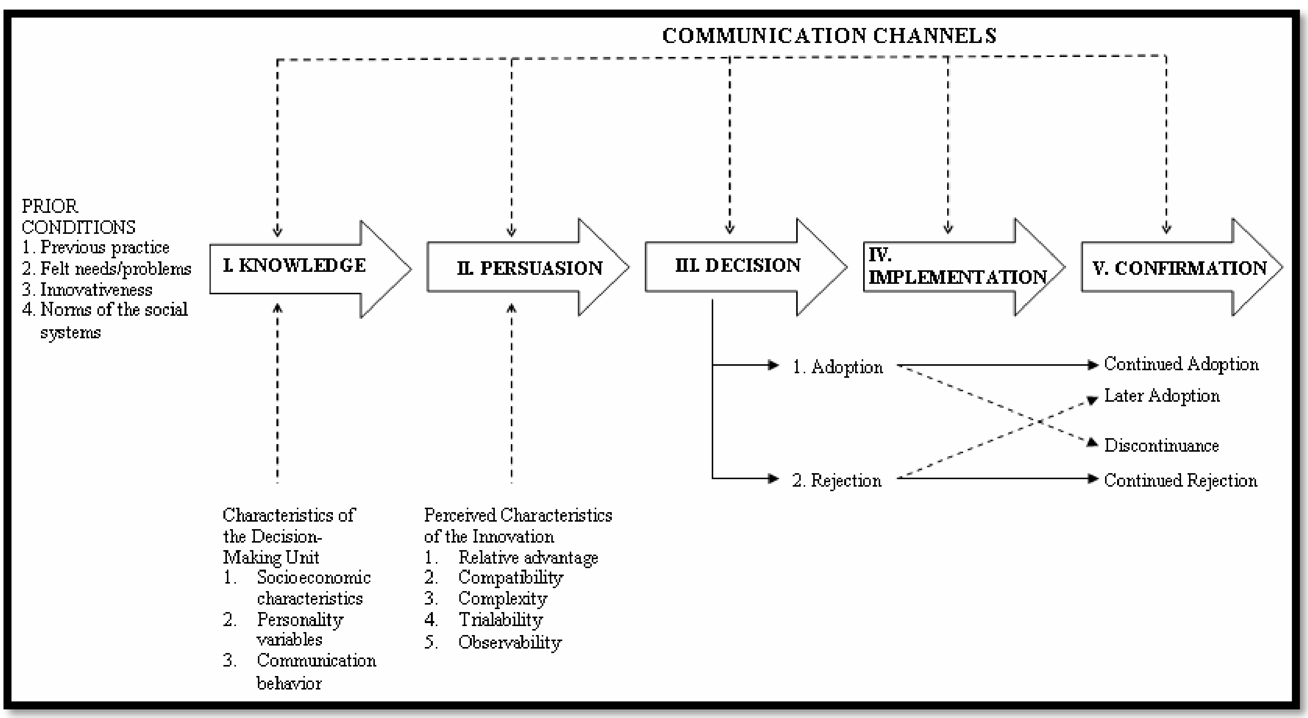

Figure 3: Diffusion of Innovation (DOI) Theory
Source: (Rogers, 2003)

2.5.3. The Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT model (Venkatesh et al., 2003) was an attempt to integrate several technology adoption theories in which considered to be the most predictive, among which TAM, Theory of Reasoned Action (TRA), Social Cognitive Theory (SCT), Theory of planned behaviour (TPB) and others into one mode that absorbs produced results and the main influencing factors of adoption. With this fine-tuning process, UTAUT aimed to attain a comprehensive understanding of the predictive relationship between the user's behavioural intention and the actual usage behaviour (Dwivedi et al., 2017) thoroughly applicable in all contexts. UTAUT model presents four independent predictors namely, Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) which directly influence the users Behavioral Intention (BI). Besides, considering gender, age, experience, and voluntariness as variables that mediate this relationship (Venkatesh et al., 2003). Performance expectancy reflected individuals' beliefs in the usefulness of the introduced technology in enhancing job performance. Effort expectancy is the perception about the level of ease; Social influence is "the degree to which an individual perceives that important others believe he or she should use the new system; while facilitating conditions concerns about the favourable organizational and technical infrastructure (Venkatesh et al., 2003).

Hereafter, UTAUT has been intensely applied in IT adoption research with a variety of contexts. However, several studies that exploited UTAUT showed some limitations. Among these, those mediators are presuming a specific study set that might not be always available and a vast percentage of those mediators were dropped (Venkatesh et al., 2012). Also, it was argued that the relationships between study constructs lack inclusiveness (Dwivedi et al., 2017; Venkatesh et al., 2016), for instance, social-cultural index. However, towards improving its explanatory and validity, (Venkatesh et al., 2012) developed UTAUT2 (see figure 4) extending the original model by adding three additional variables; price value, hedonic motivation and habit and exclude voluntariness as a mediating variable.

2.5.1. Technology, Organization, and Environment (TOE) framework

TOE technology diffusion model (L. Tornatzky et al., 1990) is considered as an organizational level theory that provided a ground base to test adoption determinants from three contexts, organizational, technological, and environmental. While the TOE model is consistent with other theories (e.g. DOI), however, it distinctly organization-oriented and provides a stronger theoretical ground by incorporating environmental context (Awa et al., 2017; Gangwar et al., 2014).

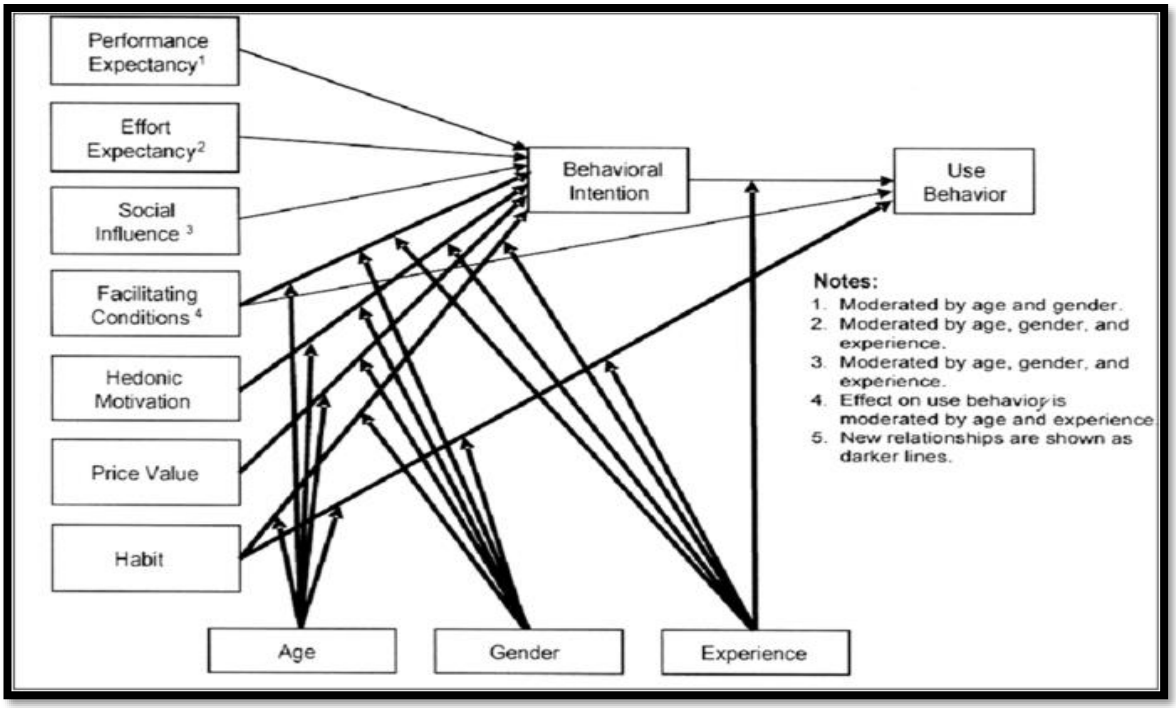

Figure 4: The UTAUT Model
Source: (Venkatesh & Bala, 2008)

TOE has shifted the prevailing attention from perceptual factors to multidimensional functional ones that can fit variant contexts with fewer restrictions. Besides, it provides a holistic approach to assess the factors that influence IT innovation-adoption decisions and development opportunities (Gangwar et al., 2014; H. F. Lin & Lin, 2008).

Technological context addresses internal and external technological variables at the individual and organization level. The examined innovation attributes are evaluated against the adopting organization technological characteristics to assess the overall technological fit. This process enables the adopter to learn about the advantages that organization might have upon accepting investigated It innovation (Rand Hani Al-Dmour, 2014; Oliveira & Martins, 2011), on other hand, it assesses the existing technological characteristics measures that either facilitate or hinder the adoption of IT innovation (Cao et al., 2014; Troshani et al., 2011). Organizational context refers to factual organization characteristics, structure, and processes in which may obstruct or smoothen the implementation of IT innovation (Cao et al., 2014). For instance, research has considered management support, communication process, size, culture, facilitating condition, trust, human capital, and other significant indicators of organization adaptiveness (Gangwar et al., 2014; Yang et al., 2015).

The environmental context concerns the climate and circumference in which the organization conducts its business process, with more focus on external factors such as competition, government policies, industry structure. It is argued that environmental factors are the most important among the other contexts and may work either in favour or against adopting IT innovation opportunities (Oliveira & Martins, 2011; Troshani et al., 2011). For instance, rapidly changing and growing industries are more innovation-oriented and may pose a higher competitive on organizations innovations (L. Tornatzky et al., 1990). Swiftly changing global policies (e.g., climate change policies) and governmental policies are other forms of environmental factors that may lead to accepting innovations. Moreover, unenforceable circumstances, for instance, the COVID-19 pandemic played a significant role in forcing organizations to seek and adopt IT innovations that support distance-work, distance-learning and virtual interaction.

TOE framework has received several critics among which, it does not provide a comprehensive conceptual framework to assess innovation adoption rather than a taxonomy that just categorizes adoption factors and contextual variables are changing based on user priority (Gangwar et al., 2014; Y. M. Wang et al., 2010). Besides, distinct from other models it ignores an individual's perception of innovation, behavioural, and competency factors.

2.6. IT ADOPTION IN HRM RESEARCH

Observing decades of HRIS research, it is noticeable that the phenomenon of IT innovation in HRM has been widely researched and received a decent amount of attention since then. This can be justified by the significant and rapid impact that information systems have had on HR functionality since its early emergence phase. Researchers have approached this phenomenon from two perspectives, the first in which had the greater share of research was directed toward understanding the impact that HRIS has had on HR functionalities and organizations, its applications, and specifications. The second was directed toward understanding its adoption determinants and factors. Therefore, the thirst to maintain competitiveness, enhancing HR services, understanding its adoption, acceptance factors, and the attuite of HR professionals and organizations toward it, had become a spirited research area. The early focus was directed toward HRIS implementation and adoption, however, after the invention of the internet and e-business started to gain more attention, this focus has noticeably shifted toward e-HR and its implementation within HRIS.

Researchers have investigated IT adoptions in HRM from a different perspective, for instance, sectorial perspective such as public sector (Troshani et al., 2010, 2011), or private sector (Alam et al., 2016; Rahman et al., 2016; Voermans & Van Veldhoven, 2007), others have investigated its adoption on the national level (Al-dmour & Shannak, 2012; Panayotopoulou et al., 2010; Strohmeier & Kabst, 2009); while others focused on organization characteristics (Lippert & Swiercz, 2005; Yusoff et al., 2015). This section aims to explore some of the previous studies which are relevant to this research and had an influence on articulating the research conceptual framework.

- Al-Mobaideen et al., (2013) study investigated the Factors Influencing HRIS adoption in Jordan-Aqaba Special Economic Zone Authority (ASEZA). They have developed a conceptual framework that extended the TAM model adding additional variables in which include Information Technology Infrastructure (ITI), Top Management Support (TMS), and Individual Experience with Computer (IEC). The study revealed that only ITI had a significant influence on HRIS adoption, while perceived ease of use (PEOU) and perceived usefulness (PU), TMS, and IEC did not demonstrate a significant association. Moreover, demographic characteristics had no significant statistical differences in HRIS adoption.
- Al-Dmour, Love, and Al-Debei (2016) have surveyed 236 listed companies as an attempt to develop a comprehensive understanding of internal and external factors that predict the adoption of HRIS in the Jordanian market. in their effort to identify key factors in which associated with HRIS adoption at the organizational level, they performed content analysis across previous studies to detect literature contribution. The study has identified sixteen internal environment variables that argued to be associated with HRIS adoption and categorized it into five constructs namely: network externalities, organizational dynamic capabilities, organizational structure, management commitment, and socio-demographic profile. Besides, four external variables were identified, availability of IT suppliers and activities, competitive pressure, social influences, and government policies and support.
- In his study (S. M. Obeidat, 2016) utilized the UTAUT model to assess the mediating factor of behavioural intention between adoption determinants namely performance expectancy, effort expectancy, and social influence on actual use of e-HR. Besides, investigate the influence of e-HRM use on HRM effectiveness, the suggested framework was tested in the telecommunication industry. The results support UTAUT assumptions by (Venkatesh et al., 2003), that performance expectancy and social influence have an indirect effect on the actual use of IT innovation (e-HR

in this study) through behavioural intention, effort expectancy had no significant association with behavioural intention and e-HRM use.

- Voermans & Van Veldhoven, (2007) conducted a case study that investigated the attitude toward e-HR at Philips (Electronics) Netherlands. The study aimed to assess the attitude towards e-HR from two main perspectives, the first is IT experience at the individual level grounded on the TAM model with three constructs, EOU, usability, and user support. Second, is the influence of preferred HR role with attitude toward e-HR using (Ulrich, 1997b) HR roles constructs strategic partner, change agent and administrative expert, and employee champion. The result showed that EOU had no significant positive association with attitude toward e-HR, thus, usability and User support indicated a significant positive influence on the surveyed sample attitude toward e-HR. from HR roles perspectives, the surveyed sample with a strong preference for administrative expert HR role had no significant influence on the attitude towards e-HR, while strategic HR roles preference (strategic partner and change agent) have indicated a significant positive influence on the attitude towards e-HR. Contrary, the employee champion HR role preference showed a significant negative association with the attitude towards e-HR. (Voermans & Van Veldhoven, 2007).
- Yusoff et al., (2015) have conducted an empirical study among e-HR users to investigate attitudes toward e-HR adoption at the individual level. The study proposed framework that extended TAM by combining e-HR trust and Ulrich's HR Roles theory. The result revealed that PEOU, PU, and e-HR trust showed a significant positive influence on users' attitude towards e-HRM. From an HR roles perspective, only strategic partner and change agent had a significant positive influence on users' attitude towards e-HRM. while administrative expert and employee champion showed no association.
- Lippert and Swiercz (2005) have tackled the phenomenon of technology trust from the perspective of HRIS implementation. Driven from the increased investment in HRIS among organizations, the development of HR cross-functional integrated systems specifically enterprise Resource Planning (ERP), and the emergence of self-service HR management solutions, the study aimed to investigate the relationship between individual technology trust factor and HRIS implementation. The study proposed a framework that categorizing all possible factors with an influence on technology trust into three categories. First, organizational factors include organizational trust, pooled interdependence, organizational community, and organizational culture. Second, technological factors include technology adoption, technology utility, and technology usability. Last, individual

factors include socialization, sensitivity to privacy, and predisposition to trust (Lippert & Swiercz, 2005).

- Rahman, Qi and Jinnah (2016) applied the UTAUT model to investigate the HRIS adoption factor within the banking and financial sector. Results indicated that social influence and behavioural intention possesses a significant positive association with actual adoption behaviour, while no significant relationship has been found between effort expectancy, facilitating conditions and performance expectancy with behavioural intention to adopt HRIS.
- Among the studies that considered HR role perspective in adopting HRIS and e-HR is (Panayotopoulou et al., 2010). By analyzing data in which collected from 4,300 companies from 13 European countries, the study aimed to perform a comparison between European countries adoption of e-HR adoption by assessing the national Background factor. Further, explore the determinant of e-HR from organizational and HRM contexts. National Background context consisted of three variables, national Culture, economy, and Internet Penetration, while Organizational context consisted of size, workforce educational level, and firm performance. HRM context included factors that reflect the centralization of HRM functions, the role of HR, and internal communication. For better comparison better, surveyed countries were categorized into three clusters, namely "Northern European", "Central European" and "Southeastern European" based on their socio-cultural and geographical similarities. The result showed variation in HRIS and e-HR deployment among countries and significant variation in adoption determinants. For instance, Northern cluster countries had an average and less HRM functions deployment of HRIS than other countries, yet higher e-HR deployment. Further, Organizational and HRM factors appear to be stronger for southeastern Europe were size, centralization of HRM, internal communication, and HR role demonstrated higher predictive power.
- Gueutal et al., (2009) conducted a cross-national study that investigates e-HR adoption factors at 2,336 organizations in 23 European countries. The study suggested general factors in which consisted of size, industry, demography, work organization, employment structure, and HRM configuration, and contextual factors specifically the national business system. HRM configuration comprised institutionalization, comprehensiveness, and strategic orientation. Findings reflected the prevalent implementation of e-HR where two-thirds of surveyed organizations had it in use. Thus, an obvious variation in cross-national e-HR adoption with "Eastern post-communist countries" take the lead (Strohmeier & Kabst, 2009). Moreover, general factors namely size, work

organization, and configuration of HRM showed to be the strongest determinants of e-HR adoption.

- Robinson, (2019) conducted qualitative research to assess HR practitioners attitudes and perspectives towards the adoption and use of AI technology in the hiring process and to understand in this way. To do so, interviews with HR executives (HREs), HR recruiters (HRRs), and HR information systems analysts (HRISAs) from global organizations headquartered in the Northeastern region of the United States, were conducted. The study revealed that while HR practitioners acknowledged the relative advantage of AI-based hiring, they also acknowledge the value of human contact for successful recruiting outcomes. Moreover, HR practitioners' personal beliefs and feelings about AI, organizational change experiences, social or environmental observations, technology use framed their perspectives. the study recommended HR practitioners will need both academic and professional development training to design and support the automated workplaces of the future where human and artificial intelligence work together.

The above-listed studies are an illustration of significant previous contributions to the IT innovations diffusion in HRM research. As addressed earlier, the research of AI adoption in HRM various functions is very limited, this study. Except for (Robinson, 2019), it is obvious that the phenomenon of AI adoption and acceptance among HR leaders and organizations is missing. (Robinson, 2019) presented a variable opinion, inputs and a footstep for future research, thus, it employed a qualitative research strategy without representative statistical evidence. It is argued that the qualitative approach goes beyond the limiting human subjective glimpse to the core objective true reality and very useful in the early stage of emerging phenomenons. However, the nature of the addressed research questions and objectives were developed to provide inputs based on measurable statistical relationships.

Similar to any other similar study of which initiate the investigation of a phenomenon, the investigation must have an onset based on analogous phenomenons which may possibly share similar characteristics and then support or negate this possible resemblance in terms of explaining the underlying factors. From this study perspective, it noticeable that previous investigations of IT diffusion in HRM (e.g. e-HR, HRIS) have overweighted the economic, functional, technical and organizational factors. on the other hand, other sectors of which received the earlier AI adoption research results have underweighted these factors in favour of normative and individual adoption factors such as culture, work style and trust in technology. Therefore, this research had to kind of balance between addressing both factors to produce a reliable outcome that could form a solid base for future investigations of the phenomenon of AI contribution to the HRM. Accordingly, this research development was much influenced by the factors of which consistently showed within the previous investigations to be consistent determinants of IT adoption in HRM. Moreover, the relevant AI and automation adoption literature within the various economical aspects. From a geographic perspective, it is noticeable that Middle east HRIS and e-HR research have belated other regions in which could be described as developed countries (e.g. USA, East-Europe). It was justified in some research by lag behind in terms of software and hardware development. However, indicators show that the broad investment by big international companies in the Middle transferring home-based technologies have contributed to bridging this gap of IT diffusion and adoption, hence, support the generalization of recent Middle East IT diffusion research to a certain scale.

All these inputs from previous literature have contributed to setting the foundation of the research framework. The next chapter will elaborate on explaining the research conceptual framework by showing the investigated relationships between the various research constructs.

3. CONCEPTUAL FRAMEWORK

3.1. INTRODUCTION

To achieve the research objectives, in the previous chapter the studies and related literature in which tackled the phenomenon of IT innovation diffusion and adoption within HRM functionality were reviewed. The variation in the conceptual, organizational, and environmental contexts between the reviewed literature were visible. Moreover, it was noticeable that the development of technology adoption theories and research perceptions about the significance of adoption factors were tied with the technological advances over time. Hence, the research emphasis was fluctuating between initially focus on internal dynamics and business processes, internet emergence and the shift to external factors, and power of individual perception. The aim was to gain a comprehensive increased understanding of the research topic to develop a valid conceptual framework that direct the research effort toward achieving these study objectives. The conceptual framework provides an integrative overview that attaches the factors 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 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 this research is on examine innovation characteristics factors, individuals trust in technology, and internal organization structure. The proposed conceptual framework represented below (Figure 5) 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 of previously recognized and verified IT innovation diffusion theories namely, Diffusion of Innovation Theory (DOI), and Technology-Organization-Environment (TOE) framework, and (Ulrich, 1997b) HR-Roles theory. It is important to cite that all factors 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.

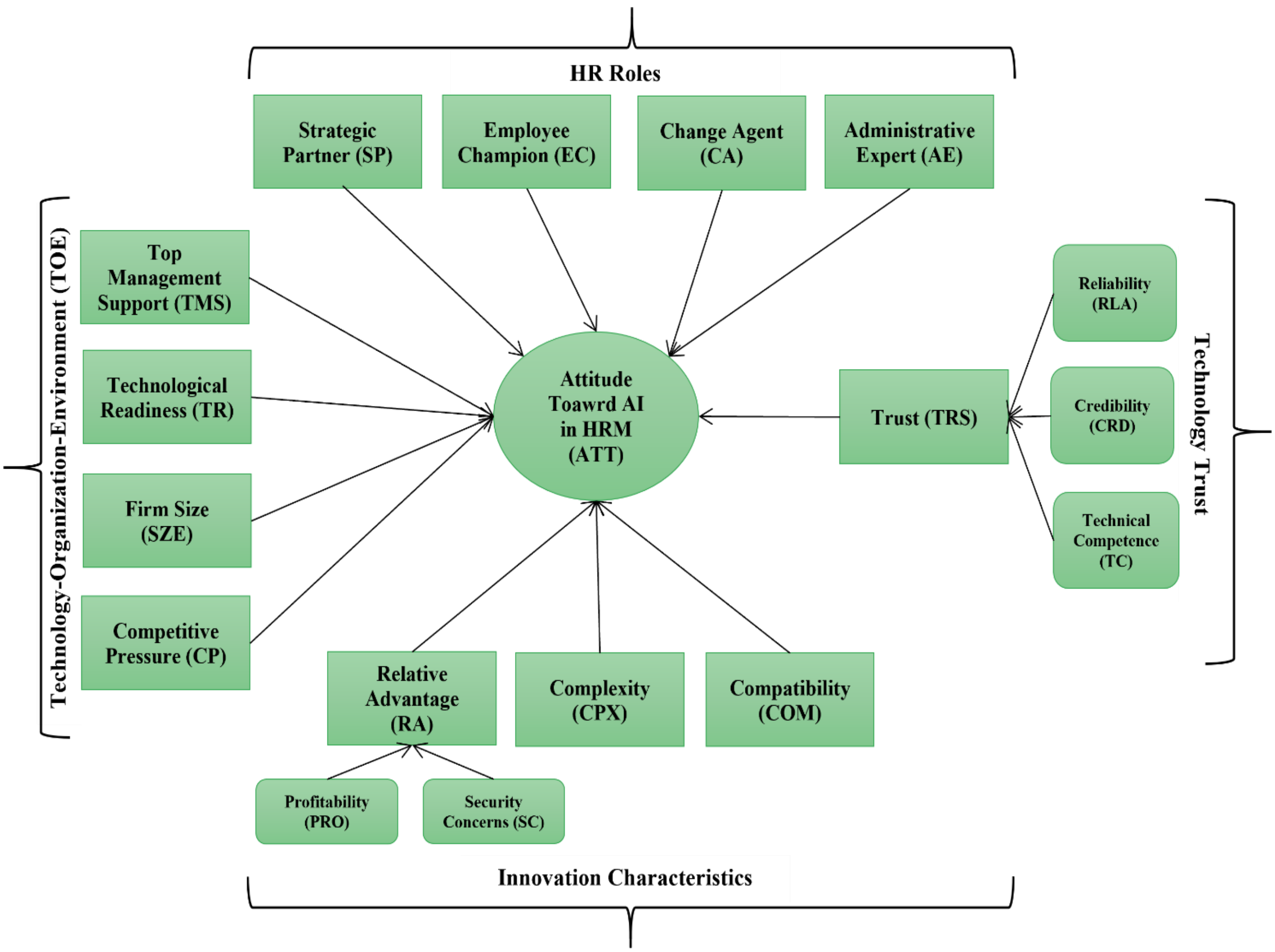

Figure 5: Research Conceptual Framework
Source: Author's Construction

3.2. RELATIONSHIPS AND HYPOTHESES DEVELOPMENT

The final research framework and research methodology was the result of research efforts during the researcher first early years of PhD studies. After acquiring a conceptual comprehensive understanding of the research phenomenon during the first year (2018), preliminary research was conducted to gain field advanced insights and initially validate the research variables, approach, and instrument. The preliminary research was conducted during the second quarter of 2019 among HR professionals who are members of the Jordanian Human Resources Management Association (JHRMA), and part of the results was published (Hmoud & Várallyai, 2020) while others were presented at the Károly Ihrig Doctoral School of Management and Business Conference for PhD Students. The preliminary research has had two major significant contributions, first, to the development of research theory and framework and critical revision was made to the study variables, relationships and hypothesis based on the analyzed data and feedback. The second is in research procedures such as population and sampling selection, instrument development and wording process. In this section, the research constructs and the underline factors are defined with their hypothesized relationship are highlighted and furtherly discussed.

3.3. INNOVATION CHARACTERISTICS

Within his Diffusion of Innovation theory, (Rogers, 2003) has defined five characteristics of innovation as perceived by individuals in which help to explain their different rates of adoption, relative advantage, compatibility, complexity, trialability, and observability. However, IT innovation adoption research have argued that the more advancement of technology is recognized the more trainability and observability are losing their importance. Consequently, the general IT adoption literature and HRIS in specific have been emphasizing relative advantage, compatibility, and complexity as substantial innovation characteristics in which had significant association with the adoption decision.

3.3.1. Relative Advantage

Relative advantage is defined as “is the degree to which an innovation is perceived to be better than the idea it supersedes” (Rogers, 2003). When the prospective adopter perceived that a particular innovation has a higher relative advantage in terms of fulfilling their needs, its diffusion would be faster than other alternatives. The determinants of the relative advantage are linked with the nature of the innovation, for instance, social benefits, economic profitability, security concerns, increased comfort, time saved, facilitate the decision-making process, or generally improved efficiency and effectiveness (A. Lin & Chen, 2012; Rogers, 2003). However, to acquire a perception about the relative advantage of innovation, prospective adopter ought to learn and understand the innovation qualities whether in theory, or from THE competitor’s observation, or have actual practical experience.

Relative advantage is comparable to Perceived Usefulness (PU) and Perceived ease-of-use (PEOU) of the TAM model and performance expectancy (PE) of the UTAUT model (Yang et al., 2015). Out of 25 characteristics of innovation, Louis Tornatzky & Klein, (1982) revealed that relative advantage, complexity and compatibility are the most consistently associated with innovation adoption. Besides, earlier research (Kendall et al., 2001; Premkumar & Roberts, 1999; Ramamurthy & Premkumar, 1995; L. Tornatzky et al., 1990) argued that Relative advantage is among the of the best predictors and consistently showing the positive influence on innovations adoption and diffusion.

IT innovation adoption studies (L. F. Chen & Chien, 2011; Oliveira et al., 2014; Premkumar & Roberts, 1999; Puklavec et al., 2018) have intensely examined the user-perceived relative advantage association with IT innovation adoption, and have exhibited that relative advantage of an IT innovation is one of the most consistent positive predictors used in IT adoption research. The presence of the relative advantage factor is obvious within both early and contemporary emerging IT adoption research. For instance, Electronic Data Interchange (EDI) (Kuan & Chau, 2001; Premkumar & Ramamurthy, 1995; Soliman & Janz, 2004), e-business (Chenhui, 2004; Grandon & Pearson, 2004; Jungwoo Lee, 2004; Musawa & Wahab, 2012; To & Ngai, 2006), Radio Frequency Identification (RFID) (Chong & Chan, 2012; Y. M. Wang et al., 2010), cloud computing (A. Lin & Chen, 2012; Low et al., 2011; Oliveira et al., 2014; Yang et al., 2015), business intelligence (Chaveesuk & Horkondee, 2015; Puklavec et al., 2018; Zaied et al., 2018). From an HRIS perspective, relative advantage refers to the expected usefulness and benefits of HRIS to HR processes efficiency and effectiveness. Like other organizational functions, there is no doubt that IT has significantly improved the effectiveness of an HR department and contributed to grant HRM increased strategic importance within the organization. Literature (Ahmer, 2013; Al-Dmour Rand, Masa'deh Ra'ed, 2017; Alam et al., 2016; Parry & Wilson, 2009; T. Teo et al., 2007) have investigated the perceived relative advantage of HRIS, and it has been consistently found to be a strong positive predictor of HRIS adoption. The relative advantages of AI technology in HRM are being extensively promoted by the vendors. For instance, among the elaborated suggested AI advantages in HR are automating administrative tasks, time-saving, cost efficiency, employer branding, accuracy, eliminating bias, quality, instantaneous services, and improved customer satisfaction. Robinson, (2019) qualitative research on understating HR practitioner's attitudes toward AI in hiring, have investigated HR practitioner's perception of AI relative advantage themes established based on their feedback about the HR systems they had replaced or were in the process of replacing. The seven themes are Technology costs and ROI, new versions of the technology, managing the overall recruitment process, AI in interviewing, AI and human contact, job roles, demographics. The results (summarized in Figure 6) revealed that in five of the seven themes, participants identified the relative advantage of using AI, however, three out of those five areas indicated situational relative advantage (dotted lines) where it may or may not exist. Two areas revealed a slight or no relative advantage of AI technology (dashes and dotted lines) (Robinson, 2019).

From these results, it is observable that HR practitioners have perceived relative advantages at administrative analytical augmented Intelligence such as sourcing and screening, yet the lack of relative advantage or trust in AI at intuitive autonomous intelligence level, such as interviewing and human contact. Researchers (Benlian & Hess, 2011; Martins et al., 2016; Oliveira et al., 2014) have argued that IT innovations profitability in terms of cost-saving and security concerns are among the most important features in which determines its relative advantage. Generally, there is a noticeable gap in HR AI adoption research and a lack of empirical evidence about HR practitioner's perception of previously defined relative advantages. Therefore, this study aims to examine the influence of perceived profitability and security concerns on HR Leaders' perception of the relative advantage of AI applications in HRM. Moreover, the prediction relationship between HR leaders' perception of AI relative advantage and their attitude toward it.

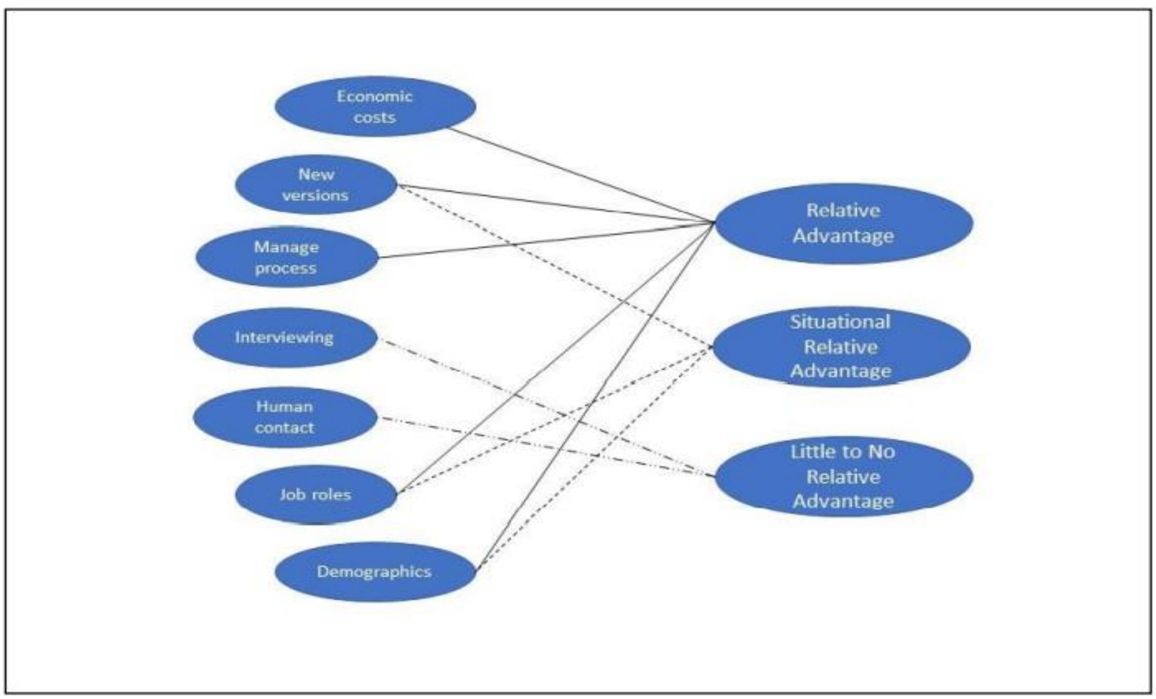

Figure 6: Themes of Relative Advantages of AI in Hiring
Source: (Robinson, 2019)

3.3.2. Complexity

Complexity is the DOI theory innovation characteristic which consistently recognized to affect the adoption rate of innovations. Rogers, (2003) defines complexity as “the degree to which an innovation is perceived as relatively difficult to understand and use” and it represents user perception about the innovation under question (Rogers, 2003). Gopalakrishnan & Damanpour, (1994) have argued that complexity includes multiple concepts. First, the extent of divisibility of innovation and the capability to apply the innovation on a limited basis where higher divisibility reflects lower complexity. Second, the intellectual difficulty linked with understanding the innovation, “as in differences between conventional and advanced technology. The greater the sophistication and the newer the knowledge base, the higher the complexity of the innovation” (Gopalakrishnan & Damanpour, 1994). Lastly, complexity reflects the degree of newness and originality of the innovation, the newer and more original innovation, the higher complexity perceived by the potential user (Gopalakrishnan & Damanpour, 1994). While all other DOI model innovation characteristics (relative advantage, compatibility, trialability, and observability) have a positive relationship with innovation adoption rate, complexity is negatively related to adoption (Low et al., 2011). Complexity is the inverse of ease of use (EOU) within the TAM model. From the IT perspective, greater perceived complexity may cause higher uncertainty about IT success and higher perceived risk associated with its adoption. Further, complexity might have resulted from the potential user lack of knowledge, skills, and ability to seamlessly understand the characteristics of an IT innovation, hence, leads to higher resistance (Rand H. Al-Dmour et al., 2016). Complexity has been empirically proven to be a significant factor in IT adoption research. For instance, cloud computing (Martins et al., 2016; Palos-Sanchez et al., 2017), business intelligence (Rouhani et al., 2018), HRIS (Al-Dmour Rand, Masa’deh Ra’ed, 2017; Rand H. Al-Dmour et al., 2016). Thus, in contrary several IT adoption determinant researches such as HRIS (Ahmer, 2013; T. Teo et al., 2007), cloud computing (Low et al., 2011; Oliveira et al., 2014), e-HR (Wickramasinghe, 2010), business intelligence (Sujitparapitaya et al., 2012) have not found a significant association between complexity and IT adoption.

The modern utilization of AI in other functions such as in Operation Management (OM) and finance, promises to amplify employee’s intelligence, solve complex tasks, and firmly support the decision-making process (Grover et al., 2020). Observing literature and internet reports, HRM major focus so far is directed toward the AI contribution in automating the time-consuming process and support the HR decision-making process. For instance, talents sourcing, screening, and communication through

ATS and CRM solutions. Incorporating AI in advanced complex tasks within the HRM is presented at the theoretical level, and surveys reflect a noticeable reliant and cautious attitude toward it by both, HR practitioners and users (Premnath & Arun, 2020; Wright & Atkinson, 2019). Further investigation is needed to understand the rationales behind this phenomenon, and whether the know-how and complexity of AI have a role in cultivating this conservative mindset or inhibits its adoption. When applying (Gopalakrishnan & Damanpour, 1994) definition of complexity on conventional HRIS methods and AI HR systems, it can be claimed that AI has lower divisibility, higher intellectual difficulty linked with understanding its data processing, and more newness than HRIS, therefore, higher complexity is assumed. Conventional HRIS has higher trainability where HR practitioners could be trained to understand its methodological approach and even alter its data exploitation processes. However, while AI human resources applications have a simpler user interface and it aims to mitigate the complexity of the decision-making process, thus, a higher complexity in term of its methodologies. For instance, it would more complex for HR practitioners to understand AI techniques (e.g., machine learning, Neural langue), and explain how the results are produced. This know-how phenomenon institutes a key challenge for HRM, especially when advocating ethical practices, error-free, and unbiased outcomes. Another complexity may emerge when deciding where to apply AI and at which tasks level to maintain the best-desired deployment. While AI institutes a major change to the current methods in processing HR tasks, organizations may be less likely to adopt if it requires acquiring new high-level skilled talents to operate. While complexity was acknowledged to negatively affect the rate of adoption, this research aims to assess HR practitioner's perception about the complexity of AI in HRM and its effect on their attitude toward it while assuming a negative relationship.

3.3.3. Compatibility

Compatibility is defined as "the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters" (Rogers, 2003). In his Diffusion of Innovations (DOI) theory, (Rogers, 2003) emphasized compatibility as one of five main innovation characteristics that influence its diffusion and thus it was previously emphasized as An important factor that affects adapter perception when assessing workplace automation. Although AI in HRM promise to offer a breakthrough and might be perceived as technically efficient in processing HR tasks, however, when it comes to adoption, it might not happen if the potential adopter perceives it as incompatible with existing practices and needs or incompatible with socio-culture values and beliefs.

(Rogers, 2003) addressed compatibility by highlighting two dimensions: values of the adopter and practices of the adopter (Moore & Benbasat, 1991). From the literature, it was noticed a variety of dimensions in the researcher's interest in assessing innovation compatibility. For instance, while Tornatzky & Klein (1982) addressed normative compatibility which concerns the values and norms, and operational compatibility in which addresses current practices and its compatibility with new proposed innovation or technology, Premkumar & Ramamurthy (1995) focus on compatibility with the on-hand hardware/software referring to it as technical compatibility and viewed values and existing practices as organizational compatibility (Y. S. Wang et al., 2016). Besides, the extent of technical compatibility with currently in use HRIS, information technology infrastructure and expertise, represent the technical compatibility that may crucially influence the attitude towards adoption decision. Also, compatibility entails the firm technological strategic alignment such as the technology cost with the AI hiring applications (Rand H. Al-Dmour et al., 2016).

Researchers (Al-Dmour Rand, Masa'deh Ra'ed, 2017; Grandon & Pearson, 2004; A. Lin & Chen, 2012; Taylor & Todd, 1995; T. Teo et al., 2007) showed that high compatibility is an essential factor that separates adopters from non-adopters and has been identified as a facilitator for the adoption decision. For instance, Yang, Sun, Zhang, & Wang (2015) results showed a significant role of compatibility in adopting software-as-a-service (SaaS). Besides, researchers (Das & Dayal, 2016; A. Lin & Chen, 2012) have found that compatibility is a significant positive determinant in user attitude toward cloud-computing adoption. From an HRIS perspective, (T. Teo et al., 2007) found that compatibility positively influences the decision to adopt HRIS. Al-Dmour Rand, Masa'deh Ra'ed, (2017) in their study that investigates firms' internal and external environmental factors in which influence their adoption and implementation of HRIS within shareholding companies in Jordan, showed that compatibility is among the important factors. Moreover, in (Robinson, 2019) qualitative research on understating HR practitioner's attitudes toward AI in hiring, participants have highlighted the importance of AI compatibility with the company strategy, current HRIS practices, and organizational culture, as a precursor for its acceptance.

AI-based solutions embody a significant change in existing conventional HR practices. Therefore, the computability of organization norms and values with the proposed change is crucial. For instance, an organization with innovative driven strategic direction might perceive an AI-based solution as an opportunity, while on other hand, an organization in which value certainty and best practices might have a different attitude toward adopting AI applications resulted from incompatibility with the organization socio-cultural values and beliefs and current or previously introduced work processes and procedures (Rogers, 2003). The extent of compatibility with currently in use HRIS, information technology infrastructure and expertise represent the technical compatibility that may crucially influence adoption decision. Also, substantial changes in work processes and practices may trigger employee’s resistance in reaction to the newly introduced procedures, which might influence the organization adoption of the HRM AI solution. In emerging AI-based HRM systems, data administration and maintenance where data storage and analysis are mostly carried out by service providers and users are granted access to use the service without carrying any hardship in terms of technical components. Dissimilar to conventional HRIS practices AI solutions are mostly Software-as-a-Service (SaaS)- or cloud-based HR systems, and their employment consists of a feasible alternative to the On- facility HR systems that required technical hardware installation. Several studies (Low et al., 2011; Martins et al., 2016; Oliveira et al., 2014) of which assessing emerging IT innovation adoption have found no significant effect of compatibility on adoption decision. Therefore, between the two concepts of compatibility: normative and technical compatibility, this study emphasizes that normative compatibilities significant for HR Leaders’ attitude toward AI systems rather than technical compatibility. Emphases are placed on the level of variation between current practices and AI-based solutions, their compatibility with current policies and values, and HR leaders’ willingness to radically change their current practices, for instance, the automation of the CV screening process.

3.4. TECHNOLOGY TRUST

Trust is defined as the “ psychological expectation that a trusted party will not behave opportunistically, and the willingness of a party to be vulnerable to the actions of other parties” (G. Kim et al., 2009; Mayer et al., 1995). Trust mediate most of the economic and social relations where uncertainty is present (Pavlou, 2003). A trust relationship has several perceptions among which, the trusted party will behave in the trustor best interest, expectations in which the trusted party to fulfil, hence, the absence of full control and a certain level of dependency exists between a trustor and a trustee. These definitions indicate that expectations, attitudes, willingness, risk, and interdependency are essential in trust (G. Kim et al., 2009). It is argued that an Individual’s trust toward a specific IT innovation is a motivational factor that will positively impact his behavioural intention to use it (Cody-Allen & Kishore, 2006). The rapid technological advancement and the emergence of internet-based business have increased the importance to understand the users' psychological aspects such as trust in

IT (Casey & Wilson-Evered, 2012; Gefen, 2002; Mcknight & Chervany, 2002). More research has introduced a conceptual structure in which incorporating the notion of trust as an attempt to explain various economic, interpersonal, and business results. Further, the trust factor relationship with IT adoption and implementation have been investigated and appeared frequently in both early and recent research. For instance, mobile-commerce (G. Kim et al., 2009; Xin Luo et al., 2010), e-government (Taiwo et al., 2012), e-commerce (Cody-Allen & Kishore, 2006; Gefen, 2002; Gefen et al., 2003; M. K. O. Lee & Turban, 2001; McKnight et al., 2002; Pavlou, 2003), e-learning (El-Khatib et al., 2003; El-Masri & Tarhini, 2017), and automation (Parasuraman et al., 2008). Within HRIS research, (Yusoff et al., 2015) study revealed a significant relationship between the attitude towards using e-HR and perceived usefulness with trust towards e-HR at multinational companies in Malaysia. Moreover, (Lippert & Swiercz, 2005) introduced 11 propositions as an attempt to explore the relationship between HRIS success and individual's trust and emphasized the role of trust in newly introduced HRIS processes.

Trust is an important factor in a human-automation relationship and researchers argued that while trust intervenes to mediate humans' interpersonal relationships, it also mediates the human relationship with technology and automation (J. K. Choi & Ji, 2015). Moreover, trust has been recognized as determining factor for users dependence and acceptance of automation by influencing the relationship between the attitudes and beliefs toward automation and the behavioural intention to use it (Gefen et al., 2003; Parasuraman et al., 2008; Pavlou, 2003). Although several theories have been instituted to explain the notion of technology trust, hence, their degree of effectiveness in assessing technology trust is controversial. In behavioural literature, the Trustworthiness factors model (Mayer et al., 1995) has been frequently appearing in organizational trust research (Evans & Revelle, 2008; Gefen, 2002; Gefen et al., 2003; Mayer et al., 1995; Mcknight & Chervany, 2002) from the perspective of users perception about system trustworthiness. Mayer et al., (1995) define three beliefs of trustworthiness, competence, integrity, and benevolence. Competence is the belief that the trusted party has the ability, skills, and characteristics to produce the expected result; Benevolence is the extent to which a trustee intention is to do good to the customer aside from solely seeking profit; Integrity is "the trustor's perception that the trustee adheres to a set of principles that the trustor finds acceptable". John Lee & Moray, (1992) investigated the trust in automation, they argued that operators opted to use automation if their trust surpasses their confidence in their ability to control, otherwise, they prefer manual control (Parasuraman et al., 2008). They defined three constructs of trust: performance, process, and purpose.

Performance describes the current and historical function of automation measured by several indicators such as reliability, predictability, and ability. Performance construct represents the competency or expertise as demonstrated by automation ability to achieve the operator's goals. The process construct describes the appropriateness of automation's algorithms for the assigned task. Purpose refers to the underlying motives or intention for which the automation is used, in other words, reflects the designer's aim in creating the system (John Lee & Moray, 1992). Later, (Söllner et al., 2011) have built on (John Lee & Moray, 1992) three-dimension (performance, process, and purpose) model, and introduced a theory of explanation and prediction for the formation of trust in IT artefacts. Söllner et al., (2011) have defined three dimensions that predict the trust in IT artefact and associated a specific set of variables (see Figure 7) that measure each dimension, the result showed a significant impact of the three dimensions on trust.

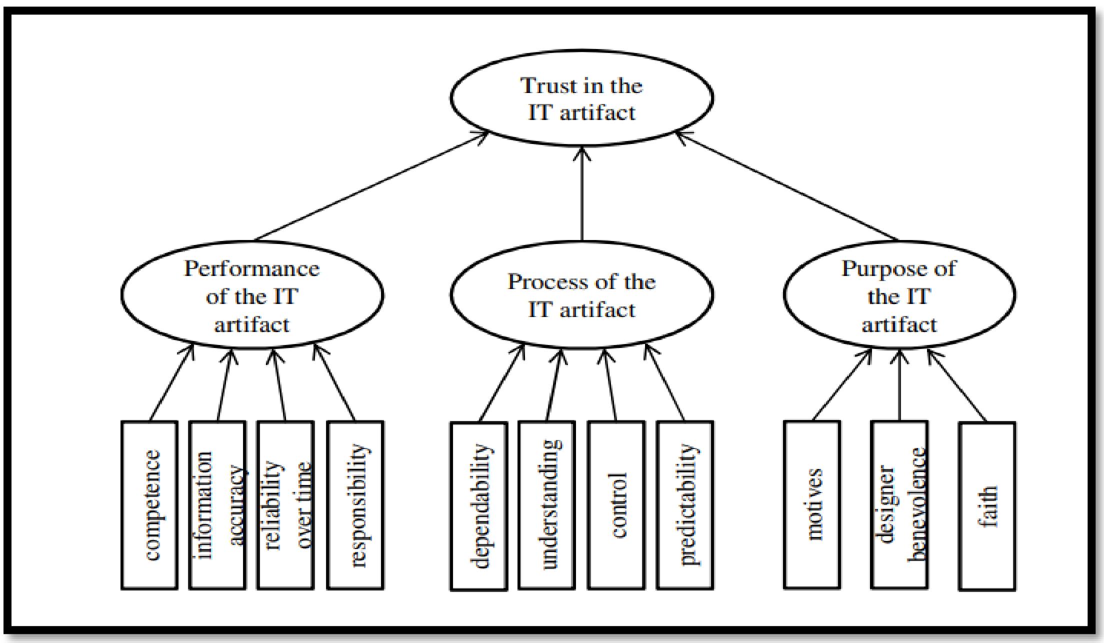

Figure 7: Dimensions of Trust
Source (Söllner et al., 2011)

Lippert & Swiercz, (2005) argued that applying organizational interpersonal trust theories (ability, integrity, and benevolence) on technology trust is questionable for several reasons among which, the difference in the directionality of the trusting relationship, human metrics do not fit anthropomorphized technology, and both forms of trust (interpersonal and technological) are influenced by the predisposition to trust, thus, predisposition varies between trusting humans and a machine. Therefore, Lippert & Swiercz, (2005) introduced a model of Trust in Information Systems Technology (TIST) which defines technology trust evaluation through the following three factors, Technology predictability: the individual’s prediction that technology will produce consistent performance and as expected. Technology reliability is an individual’s belief that technology will consistently perform in situations that involve some degree of dependence and risk. Mean in situations “where individuals depend on the technology for the completion of a job-related task, the individual is placed in a position of vulnerability if the technology does not function as expected” (Lippert & Swiercz, 2005). Technology utility is an individual’s belief, perception, and assumption about the technology usefulness. Furthermore, Thatcher et al., (2011) defined trust in IT as a reflection of user beliefs about the system’s attributes such as IT reliability or predictability. They defined three dimensions of trust each of which relates to Mayer et al., (1995) interpersonal trust beliefs. The first dimension is functionality which refers to the belief that the system has the capability, functions, or features to perform its tasks and this dimension is akin to the interpersonal competence belief. The second dimension is helpfulness belief which refers to the belief that the IT system will deliver adequate and responsive aid, and this dimension is similar to interpersonal benevolence belief. The last dimension is predictability belief which refers to the belief that the IT system acts consistently, and its performance can be forecasted, this dimension is similar to interpersonal integrity belief. Similarly, Hasan et al., (2012) have tackled the phenomenon of trust in software systems from a user’s perspective by evaluating the trust functionality, helpfulness, and reliability as follows:

- Functionality represents users’ expectations about the software systems capability.
- Helpfulness represents users’ beliefs that technology provides adequate, effective, and responsive help.
- Reliability assumes software systems are consistent, predictable, or reliable in performance (Hasan et al., 2012).

While early technology trust studies (LEE & Moray, 1994; John Lee & Moray, 1992; Moray et al., 2000; Parasuraman et al., 2008) have tackled the phenomenon of process automation trust, these studies were concerned with mechanical level automation such as industrial unit automation where users maintained manual processing option. Studies that investigate the user's trust factor of contemporary AI application in which operates at an analytical and intuitive level of AI scarce. J. K. Choi & Ji, (2015) investigated the adoption and the factors that influence user’s trust in the autonomous vehicle. They applied TAM with a defined three dimensions of trust in an autonomous vehicle: system transparency, technical competence, and situation management. System transparency is the extent to which users predict and understand the autonomous vehicles operating method. Technical competence is the degree of user perception about autonomous vehicles performance. Situation management refers to the user's belief that control can be resumed when desired (J. K. Choi & Ji, 2015). The results showed that that perceived usefulness and trust are the most significant determinants of intention to use autonomous vehicles, and the trust dimensions (system transparency, technical competence, and situation management) have a positive effect on trust (J. K. Choi & Ji, 2015). Moreover, Hmoud & Várallyai, (2020) have investigated the prediction relationship between the trust factor and the behavioural intention toward adopting AI in HRM, the result has revealed that trust is a significant positive predictor of adoption intention.

It is observable that previous studies have emphasized the significant association between technology trust and the attitudes toward adopting IT innovations and the actual use. Therefore, understanding the factor of HR practitioner's trust influence on their attitude toward these AI tools is important. There is a noticeable knowledge gap in examining the trust relationship with interactive AI-based applications such as chatbots. Madsen & Gregor, (2000) defined Human-computer trust as "the extent to which a user is confident in and willing to act based on, the recommendations, actions, and decisions of an artificially intelligent decision aid". With the increased reliance on autonomous technologies, noticeably growing research attention is allocated to address the phenomenon of AI trust (Nordheim et al., 2019). AI applications in HRM represent a new way of doing things within HRM functions, for instance, a CRM and ATS in which could take over a vast percentage of the recruiter's administrative tasks such as sourcing, screening, and evaluating talents is considered a fundamental change in HRM reliance on IT. The human-like attributes of HR Chatbots and their automated natural language interactive capability handover some of the decision-making processes which previously were made by humans to AI, therefore, it makes trust exceptionally important. de Visser et al., (2016) conducted a three experiments study to examine the effect of anthropomorphism—the degree to which an AI system exhibits human characteristics— on trust, the results showed that more anthropomorphic were associated with greater trust resilience and higher resistance to trust loss (de Visser et al., 2016). In other words, the more AI systems able to mimic human attributes, the more trusted. This result is confirmed by (Følstad et al., 2018) when assessed trust in customer service chatbots. Further, AI is argued to improve task quality such as human errors and bias within the HR hiring process, however, certain claims about AI-systems ability to learn bias or reflect programmers intentional or unintentional cultural or personal bias. Hurlburt, (2017) urges the need to investigate if HR Leaders' trust these systems when it comes to providing the best result. Moreover, HR AI-based applications tools are mostly web-based services, therefore, the degree of control, provider's commitment to the company interests, and the systems competence signifies the trust aspect. Robinson, (2018) conducted a qualitative study to understand the attitude of HR practitioners toward AI in hiring by interviewing HR executives (HREs), HR recruiters (HRRs), and HR information systems analysts (HRISAs) from global organizations headquartered in the Northeastern region of the United States. The study tackled the notion of trust in AI application, the interviewee's responses (see Figure 8) have demonstrated high concerns and conservative attitude.

Statements of "Trust" from HREs, HRRs, and HRISAs

Participants	Trust Statements
HR Executives	"Because I don't know it. I don't trust it yet." (HRE4) "I know my bias towards not liking it." (HRE4)
HR Recruiters	"I think the bias issue is a big one." (HRR3) "I'm not 100% for artificial intelligence as it relates to hiring." (HRR3)
HR Information Systems Analysts	"As stuff evolves, there are some concerns." (HRISA1) "Just because you can do it, doesn't mean you should do it." (HRISA1) "Healthy suspicion or just awareness of concerns around AI." (HRISA2) "I'm aware we can't fully rely on that." (HRISA2) "I think bias is a reality check piece." (HRISA2)

Figure 8: HR practitioners Trust statements
Source (Robinson, 2019)

In summary, it is concluded that literature has to a certain level recognized that trust of IT innovation can be classified into three dimensions which relates to early interpersonal trust beliefs. The first is that the system performance is predictable and understandable. The second dimension is the belief that the system is consistently accurate and reliable. The third dimension is the belief about system functionality, adequate, and effectiveness (J. K. Choi & Ji, 2015; Lippert & Swiercz, 2005). To assess the trust relationship with HR leaders attitudes toward AI applications in HRM, this study adopts a previously well-supported conceptualization of IT innovations trust. It investigates the HR leader's beliefs about AI **Technical competence** in HRM, this dimension reflects whether they perceive AI is capable and competent to autonomously handle time-consuming tasks proficiently and deliver the expected results. Further, HR professional's beliefs about AI **reliability**, and whether it performs consistently and predictably. Lastly, the HR leader's beliefs about AI **credibility** suggest it operates for the best of the HR department and assesses their perception about AI adequacy, ethical practices such as maintaining secure information privacy and operate in an error-free unbiased manner.

3.5. TECHNOLOGY-ORGANIZATION-ENVIRONMENT (TOE)

3.5.1. Top Management Support

Among the internal organizational factor, scholars have acknowledged top management support significance in influencing IT innovation adoption and implementation. Top management exemplifies individuals who are classified as potential decision-makers within the organization (Premkumar & Ramamurthy, 1995). In the IT adoption context, it represents those who have direct or indirect involvement in influencing organization IT strategies. IT innovation literature has identified top management support as critical in adopting and successfully implementing IT technology (Sharma & Yetton, 2003; Thong et al., 1996). Top management support is argued to drive the organization technological advancement through early adoption of IT innovation, while weak management support hinders its adoption response (Rand H. Al-Dmour et al., 2016; Chan & Mills, 2002). The adoption and implementation of new technology involve intense resources allocation, change, and user support at all levels, thus management support facilitates the smooth transition, creating a supportive climate and providing adequate resources for the adoption and implementation of new technologies (Premkumar & Roberts, 1999; Sharma & Yetton, 2003). Management, with their broader strategic viewpoints, are in a superior position to realize the advantages of IT opportunities and associated risks than the lower-level user, thus, efficiently influence the adoption attitude (Thong et al., 1996). Besides, Top management support found to be crucial for the IT systems success and acceptance, Premkumar & Ramamurthy, (1995) have surveyed 201 firms to investigate the role of inter-organizational and organizational Factors on system adoption, results showed that among organizational factors, internal need and top management support are significant to differentiate between firms with proactive decision approach to IT adoption from reactive ones. Moreover, Having a technology champion among the management team is an important factor in IT adoption (Premkumar & Ramamurthy, 1995).

Top management positively influences organizational attitude toward IT innovations through articulated organization vision (Ramdani et al., 2009). Empirically, top management support is a significant determinant for new technologies adoption. Ramdani et al., (2009) in their study on SMEs' of enterprise systems (ERP, CRM) have found that the most significant determinant in which constantly proven to be important in IS innovation adoption, is top management support. Ang et al., (2001) investigated IT usage to support total quality management (TQM) within 47 public sector agencies, the result revealed that top management support was the strongest predictor of IT adoption among internal organizational factors. Other IT innovation studies have confirmed this result, for instance, cloud-computing adoption (Low et al., 2011), software-as-a-service (SaaS) (Yang et al., 2015), e-procurement systems adoption (H. F. Lin, 2013; T. S. H. Teo et al., 2009), business intelligence adoption (Bhatiasevi & Naglis, 2018; S. Sun et al., 2018).

From an HRIS perspective, studies have extensively tackled top management support as one of the influential organizational factors. For instance, T. Teo et al., (2007) study found that top management support is only the significant dependent variable with the total number of surveyed HRIS applications. (Ahmer, 2013) have found that top Management Support and HRIS Expertise to be the top contributors to the decision of HRIS adoption. (Razali & Vrontis, 2010) examined the main factors that contributed to the acceptance of employees toward the new HRIS and concluded that top management involvement and organizational commitment are the two largest coefficients for the impact on employee's acceptance of HRIS at the Malaysian Airlines HR system (Rand H. Al-Dmour et al., 2016). Moreover, Ngai & Wat, (2006) indicated that Lack of commitment from top managers was the most frequently cited barrier to implementation of HRIS in small companies and non-adopters in Hong Kong. Rand Hani Al-Dmour, 2014) survey 236 shareholding companies in Jordan, the results revealed that top management willingness to support among the most important factors that discriminate between adopters and non-adopters.

Previous studies have noticeably associated management support with the adoption and successful implementation of HRIS and e-HR. Industry 4.0 is promoting innovation and integration at all levels, among which automation and IT utilization. Organizations in which management with a strategic orientation toward fostering an innovation-friendly climate, communicate their support, promote creativity, and offer adequate resources, are more likely to adopt new IT innovation and gain technological competitiveness. In this study context, the aim is to assess the relationship of HR practitioner's perception of the level of management support and their attitude toward AI applications in HRM. The importance of assessing this relationship is driven by the belief that, when it comes to process automation, management may show loath to support its adoption. This might be influenced by other factors such as the difficulty to understand how AI process HR tasks, in other words, the lack of the know-how the results are produced. Additionally, the management role is crucial to overcome possible resistance in which could emerge at a lower level; hence, supportive top management would signify the AI importance in today competitive market to lessen the resistance. AI-based system automation and instantaneous proceeding of HR tasks might be perceived as a radical change to the existing common methods; therefore, this study assumes that top management innovative strategic direction, their perceptions, and familiarities with the benefit of emerging AI-based technologies, attitude toward technological changes, and the likelihood to accept risk will have a significant association with HR practitioner's attitude toward the adoption of AI applications in HRM.

3.5.2. Firm Size

Organization size can be defined by several means among which the organization's capital, physical resources, transaction volumes, geographical range or workforce count (Kimberly, 1981). Organizational size has been consistently defined as a strong determinant of IT innovation adoption (Oliveira & Martins, 2010). HRIS research (Ball, 2001; Florkowski & Olivas-Luján, 2006; Hausdorf & Duncan, 2004; T. Teo et al., 2007) have supported this premise and showed a significant positive relationship between organizational size and HRIS adoption. Moreover, Strohmeier & Kabst, (2009) investigated the factors in which influence the cross-national organizational adoption of e-HRM in Europe, argued that in the context of IT adoption, the only consistent result shows the organizational size as a determinant of adoption. The premise in which could explain this repeated research agreement is that larger organizations regularly have a wider range of financial and other resources in which could facilitate their capacity to adopt IT innovations and more capability to bear investments risk (Zhu et al., 2006). Moreover, the greater need for innovation is typically linked with larger organizations size where more advantages of automation could be realized (Strohmeier & Kabst, 2009).

Despite the previous evidence that supports the significance of rim size as an adoption predictor, (Kimberly, 1981) argued that from a "theoretical sense the effects of size may depend on the nature of the innovation in question". The early organization information systems such as ERPs and HRIS have imposed an installation technical and financial hardship on companies to adopt such systems; therefore, the firm size matter in terms of usage volume and usefulness of such IT services. However, with the emergence of big data, AI, and improved connectivity, it observable that the prevalent IT services in the industry 4.0 era are shifting toward cloud computing and Software-as-a-Service (SaaS) where services are subscription on demand based. The trend of IT service places a question mark on firm size importance as an adoption determinant. For instance, companies can utilize LinkedIn hiring services in which provides AI-based sourcing capability, and the cost is based on actual use (e.g., posted jobs ads), cloud-based without any further technical implications, and similar are other AI-based HR vendors. These on-demand services features promote full accessibility for such services equal regardless of firm size. For instance, Researches (Palos-Sanchez et al., 2017; Thu Ha et al., 2020; van de Weerd et al., 2016) found no effect of firm size on Software-as-a-Service (SaaS) adoption, conversely, (Thu Ha et al., 2020; van de Weerd et al., 2016) have found that small and medium-sized companies (SMEs) are more likely to adopt SaaS systems than large companies. Moreover, (S. Sun et al., 2018) have investigated 26 adoption factors using the results of a content analysis method within big data adoption literature, thus, the firm size factor has not been mentioned frequently and not found significant in the big data adoption context (S. Sun et al., 2018). Consequently, this study aims to investigate the relationship between firm size and HR Leaders' attitude toward the adoption of AI in HRM.

3.5.3. Technological Readiness

While the compatibility factor in which previously discussed represented the normative aspect of organization compatibility with AI adoption, the Technological readiness context address technological compatibility. It represents the available organization technological characteristics for the adoption of the introduced new technology (Oliveira et al., 2014; To & Ngai, 2006). Proposed as a technological factor within the TOE model, technological readiness concerns several organizations technological aspects among which, the technology infrastructure, IT human resources expertise and competence, and the level of technology sophistication (Low et al., 2011; Zhu et al., 2006). It is argued that the aptness of these technological characteristics with the introduced new technology positively influences its adoption. Other technology acceptance researchers have recognized technological readiness user prospective rather than organizational and emphasized user openness to new IT, personality and technology usability aspects (Yang et al., 2015). For instance, (Parasuraman, 2000) defined technological readiness as "The technology-readiness construct refers to people's propensity to embrace and use new technologies for accomplishing goals in home life and at work", and developed technology readiness index (TRI) in which defines four types of users personality traits optimism, innovativeness, discomfort, and insecurity (Erdoğmu & Esen, 2011). However, this study contemplates on TOE model (L. Tornatzky et al., 1990) definition of technological readiness since individual technology perception is assessed with DOI construct (relative advantages, compatibility, complexity).

Early (Chan & Mills, 2002; Oliveira et al., 2014; Oliveira & Martins, 2010; Yang et al., 2015; Zhu et al., 2006) research investigated technology readiness influence on IT adoption and have confirmed its significance for the adoption decision. Thus, certain studies, for instance, cloud computing (Hmoud & Várallyai, 2020; Low et al., 2011; Y. Wu et al., 2013), have suggested that technology readiness may not necessarily influence IT adoption and underemphasized its effect. While IT infrastructure and HR expertise have found to affect IT adoption decision, however, observing emerging AI-based technology reflect the decrease in IT complexity in a general sense. The trend in modern services such as AI HR systems, such as chatbots are mostly cloud-based and on-demand where service provider handles data administration and maintenance processes, and the user is given access to the service with minimum technological infrastructure hardship or IT human resources expertise at the user level. Consequently, this study aims to investigate the firm technological readiness influence on HR Leaders' attitude toward the adoption of AI in HRM while hypothesizing that technological readiness is not a significant determinant.

3.5.4. Competitive pressure

AI diffusion in HRM is considered at its early diffusion phase especially in developing countries. For this reason, this research assigns more emphasis on internal factors, however, competitive pressure is perceived as such strong influential power that chape the attitudes and the decision-making process in every modern firm. Competitive pressure refers to the level of pressure perceived by the organization from its competitors (Oliveira & Martins, 2010). Among the other external factors within IT innovation adoption and diffusion research, competitive pressure has shown to be a powerful predictor (Oliveira & Martins, 2010). With the world moving toward a knowledge-based and free-market economy, experts and research suggest that competitive pressure will continue to be on the rise. Consequently, companies are facing the urge to compete through all available means (Rand H. Al-Dmour et al., 2016). IT advancement and innovation have been playing a crucial role within this race, where companies have perceived it as an opportunity for improving efficiency and quality, thus increased competitive power. Premkumar & Ramamurthy (1995) emphasized the role of new technologies adoption as a strategic necessity during the intense competition (Ramdani et al., 2009). Similar to other organizational resources and business practices, competitive pressure influenced shaping HRM from a variety of perspectives. While for instance, manpower attraction within a diverse environment have altered the firm's diversity policies and globalization pressured for internationalizing HR practices, HRIS and e-HR emergence placed competitive pressure on HR functionality within the organization. Mcmahan, (1996), investigated 130 big companies, addressed that competitive pressures forced organizations to adopt new strategies and redesigned current processes among which their HR functions to support the rapidly changing business strategies (Rand Hani Al-Dmour, 2014). Nowadays, HRIS and e-HR technologies are inevitable for organizations who wished to internally manage their HR. The use of technology has elevated HRM quality through facilitating improved HR engagement, reduce HR cost, better HR allocation, and strategically prompt organization HR branding. Therefore, lagging competitor's IT utilization and practices is perceived as a risky strategy.

Examining previous research, the influence of competitive pressure on IT innovation adoption has been under debate. While a considerable extent of empirical evidence has supported the hypothesized competitive pressure significant determinant and a powerful driver of IT adoption and diffusion, some researchers did not support this result. For instance, Low et al., (2011) study showed that among environmental factors, competitive pressure and trading partner pressure showed a significant effect on cloud computing adoption. Likewise, e-business adoption (H. F. Lin & Lin, 2008; Oliveira & Martins, 2010; To & Ngai, 2006), e-supply chain management system adoption (Lin, 2013), mobile application adoption (Chiu et al., 2017), and Business intelligence adoption (Bhatiasevi & Naglis, 2018). Contrarily, other empirical results were incongruent with this result and showed competitive pressure as an unimportant environmental factor. For instance, (Al-Dmour Rand, Masa'deh Ra'ed, 2017; T. Teo et al., 2007) showed that competitive pressure lacks empirical evidence to be a significant factor in influencing HRIS adoption. (Oliveira et al., 2014) found no statistical significance about competitive pressure influence on cloud computing adoption. Furthermore, e-procurement (T. S. H. Teo et al., 2009), mobile business (Y. S. Wang et al., 2016).

When considering competitive pressure, two aspects are to be considered, first, is the specific industry characteristics. The degree of competition pressure varies across industries and local market positions. in other words, the competition intensity increases with the number of competitors within the same market. Hypothetically, the increased innovation adoption among competitors, the higher probability of adoption among non-adopters (Rand Hani Al-Dmour, 2014). Therefore, the respondent's industry and its market value may have a control effect on HR practitioner's perception about the association of competitive pressure with the attitude toward the adoption of AI in HRM. The second is the IT innovation diffusion phase, it is argued that competitive pressure increases along with the advanced adoption phases. In other words, early adoption phases could have less significant pressure if compared with advanced phases where the IT innovation have been tested and its value is measured.

Even though AI application in HRM is at a comparatively early diffusion stage, the low-cost and cloud-based services have made it easily accessible for small and medium enterprises (SMEs) with less consideration to technological computability. Bearing in mind the fact of previous literature variation about the effect of competitive pressure, this study aims to investigate this phenomenon from the HR practitioner’s perspective to gain additional understanding about the role of competitive pressure. While the actual initial standpoint is neutral, however, this study will hypothesis the existence of a positive relationship between competitive pressure and HR practitioner’s attitude toward AI applications in HRM.

3.6. HR ROLES

The relationship between the roles of HR and IT have been under investigation as early as the emergence of IT. Debating over this relationship, the literature has two perspectives, the first has accused IT of significantly changing the role of HR, while the other, believed that the changing role of HR has emphasised IT importance and adoption. Regardless of who is right, the interconnected relationship between IT advancement and the transformation of HR is undeniable. Ulrich, (1997) pioneer researcher in HRM roles emphasized addressed the following:

> “Technology will change how work is done in general and how HR is practiced in particular. A sample of HR-related technology questions include: How will technology connect employees without face-to-face contact? How will technology change communication patterns (e.g., electronic all-hands meetings)? How will technology change specific HR practices (e.g., resumes through Internet, distance learning for training, automated performance reviews, tailored benefit programs)?”

Considering the rapidly advancing technology and even though it has been more than twenty years since posing these questions, thus, it can be said that the general notion behind the question is still valid. The IT-driven change has gained researchers attention at all levels aiming to assists organizations to prepare for the change, redesign jobs, and reinvent the organization (Hempel, 2004). From an HR roles perspective, researchers have explored the influence of the diffusion of IT innovation within the HR functionality on the evolving roles of HR (Lengnick-Hall & Moritz, 2003). Hempel, (2004) asserted that "HR professionals must be able to adopt technologies that allow the reengineering of the HR function, be prepared to support organizational and work-design changes enabled by technology and be able to support the proper managerial climate for innovative and knowledge-based organizations".

Since the emergence of HRM as a recognized function within the organization, the roles of HRM within have witnessed a major reform. For instance, from early personnel tasks to the administrative focus in the early twenty-century, then an increased operational and administrative role later at the 60s, while at the early 1990s literature somehow affirmed the importance of strategic HRM to meet contemporary organizational challenges (Panayotopoulou et al., 2007; Ulrich, 1997a). Simultaneously, HR roles literature was proactively keen to propose and define specific HR roles and competencies to help organizations prepare for the change to gain competitive advantages. For instance, early literature (Schuler, 1990; Tyson, 1987) have argued that the current prevailed administrative HR function should presume more managerial and operational role within the organization. Ulrich, (1997b) have introduced one of the well-acknowledged models of HR roles based on two axes, the strategic or operational focus and the processes or people orientated (see Figure 9). Based on the position of HR functions within these axes, Ulrich, (1997b) have defined four HR roles, strategic partner, change agent, administrative expert, and employee champion.

- Strategic Partner: emphasizes the HR should take an active role in articulating overall organization strategy by formulating the HR strategies, being involved in the strategic planning process at level organizational, align the HR practices with overall organization strategy.
- Change Agent: HR role in promoting change management, facilitator, modelling change, being a constructive advocate of change across, fostering an adaptive culture that copes with environmental changes ((e.g., IT innovation), enhance organization capacity for change and provide daily operational support for employees and manager such as problem-solving.
- Administrative Expert: addresses HR responsibility for the efficiency of HR within the organization, managing administrative processes for organization personnel.
- Employee Champion, this role emphasizes HR role in sustaining employee's commitment, ensure employees engaged, being an advocate for employees concerns, bridging the gap

between employees and management, and improve employees' commitment and their ability to deliver results (Ulrich, 1998).

Figure 9; HR Roles
Source: (Ulrich, 1997)

Researches (Hempel, 2004; Lengnick-Hall & Moritz, 2003; Panayotopoulou et al., 2007; Voermans & Van Veldhoven, 2007) have investigated the relationship between HRIS diffusion and the changing HR role within the organization. The research settled on the positive relationship between IT diffusion in HRM and its increased strategic orientation. Throughout its diffusion, HRIS has had a significant role in downsizing and redefining the administrative and operational role, at the same time emphasizing and improving the strategic HR involvement, hence, gradually balancing the strategic and administrative participation (Gardner et al., 2003; Lepak & Snell, 1998; Panayotopoulou et al., 2007). Consequently, the strategic partner and change agent HR role preferences are argued to have a positive influence on adopting IT (e.g., HRIS, e-HR) within HR functions. Besides, since the greater early contribution of IT is to facilitate and process the administrative tasks within the HR function, the administrative expert HR role is also argued to have a positive relationship with IT adoption in HRM. Contrarily, the employee champion role is claimed to decrease the likelihood of the adoption of IT in HRM (Voermans & Van Veldhoven, 2007). The reason for this claim is the role of automation and IT involvement in reducing the classical face-to-face HR methods which are considered employee champion favourites. Voermans & Van Veldhoven, (2007) have empirically investigated the attitude towards E-HRM of 99 managers and 257 employees within Philips (Electronics) the Netherlands, incorporating Ulrich’s model to assess the relationship between preferred HR roles and their attitude towards E-HRM. The results showed that the strongest relation found is between respondents strategic

HR preferences are and their positive attitude towards E-HRM systems. Also, the employee champion role showed a more negative attitude towards e-HRM, however, no relationship has been found between the administrative expert role and the attitude towards e-HRM. Similarly, Yusliza et al., (2011) have found that administrative expert, change agent, and strategic partner had positive effects on perceived ease of use and attitude towards using E-HRM among HR practitioners in Malaysia. Yusoff et al., (2015) studied the factor in which influence the attitude toward e-HRM among 201 users and found that strategic partner and change agent have a significant effect on attitude towards using e-HRM. However, administrative expert and employee champion have no significant effect on attitude towards using e-HRM.

Driven by the scarcity of literature that assesses the association between the emphasized HR roles within the organization and the adoption of AI. This study applies (Ulrich, 1997b) HR roles framework in an attempt to assess the relationship between the preferred HR role with HR Leaders' attitude toward AI applications in HRM.

3.7. SUMMARY

To provide a comprehensive insight into the proposed conceptual framework, the following Table 2. summarizes the sub-objectives of research variables with a reference to their underlying hypotheses.

Table 2: Summarized sub-objectives of research variables

INNOVATION CHARACTERISTICS CONSTRUCT		
Variable	Objective	Hypothesis
Profitability	Examine the influence of perceived profitability on HR Leaders' perception of AI applications relative advantage in HRM.	**H1.1**
Security Concerns	Examine the influence of HR Leaders' security concerns around AI applications on their perception of its relative advantage in HRM.	**H1.2**
Relative Advantage	Investigate the prediction relationship between HR leaders' perception of AI relative advantage and their attitude toward it.	**H1.3**
Compatibility	Investigate the relationship between HR leaders' perception of AI normative compatibility with the organization and their attitude toward it.	**H1.4**
Complexity	Assess HR practitioner's perception of the complexity of AI in HRM and its effect on their attitude toward it	**H1.5**

TECHNOLOGY-ORGANIZATION-ENVIRONMENT (TOE) CONSTRUCT		
Variable	Objective	Hypothesis
Top Management Support	Investigate the influence of top management innovative strategic direction and attitude toward technological changes on HR Leaders' attitude toward the adoption of AI in HRM.	**H2.1**
Technological Readiness	Investigate the firm technological readiness influence on HR Leaders' attitude toward the adoption of AI in HRM	**H2.2**
Firm Size	Investigate the relationship between firm size and HR Leaders' attitude toward the adoption of AI in HRM.	**H2.3**
Competitive Pressure	Investigate the effect of competitive pressure on HR Leaders' attitude toward the adoption of AI in HRM	**H2.4**
TRUST CONSTRUCT		
Variable	Objective	Hypothesis
Technical Competence	Investigates the predictive relationship between HR leader's beliefs about AI Technical competence and their trust.	**H3.1**
Reliability	Investigates the predictive relationship between HR leader's beliefs about AI reliability and their trust.	**H3.2**
Credibility	Investigates the predictive relationship between HR leader's beliefs about AI credibility and their trust.	**H3.3**
Trust	To assess the trust factor influence on HR leader's attitude toward AI applications in HRM,	**H3.4**
HR ROLES CONSTRUCT		
Variable	Objective	Hypothesis
Strategic Partner	Assess the relationship between the emphasized strategic partner HR role with HR Leaders' attitude toward AI HRM	**H4.1**
Administrative Expert	Assess the relationship between the emphasized administrative expert HR role with HR Leaders' attitude toward AI HRM	**H4.2**
Employee Champion	Assess the relationship between the emphasized employee champion HR role with HR Leaders' attitude toward AI HRM	**H4.3**
Change Agent	Assess the relationship between the emphasized change agent HR role with HR Leaders' attitude toward AI HRM	**H4.4**

Source: Author's Construction

4. MATERIAL AND METHODS

4.1. INTRODUCTION

This chapter represents the adopted research methodology to answer the research questions. A research methodology is defined as a systematic approach that involves a set of guidelines, activities, and tools to produce valid and reliable research results (Sekaran & Bougie, 2016). This chapter will introduce the adopted research philosophy and approach to empirically investigate the hypothesized research framework relationships and attain the study objectives. Further, the research methodology, design, methods, tools, and procedures will be presented. Lastly, the applied data collection and analysis procedures will also be explained.

Defining Paradigms. While research philosophy represents our general and fundamental assumption about how we perceive the world, Research paradigms are defined as " patterns of beliefs and practices that regulate inquiry within a discipline by providing lenses, frames and processes through which investigation is accomplished" (Weaver & Olson, 2006). Paradigms are epistemological orientations in which shape and guide the research approach, stagy, and method. Deciding on the right research paradigm is a critical step as it set up the lens or frames in which produces the theories, principles and presuppositions that aim to understand the phenomenon in question. Three is four defined broad epistemological categories, positivism, interpretivism, critical realism and pragmatism. In social science, positivism is a highly structured research philosophy in which explores human behaviour in such a way similar to the physical and natural sciences in which study observable and measurable variables to predict outcomes in a cause and effect philosophical mindset (Saunders & Lewis, 2012). Positivism beliefs in objective truth, hence, can be replicated controlled, and generalized to provide a better understanding of the research phenomenon. Therefore, positivism emphasizes deductive reasoning to develop theories in which can be tested through fixed, preset design and objective measures while maintaining the external position (Sekaran & Bougie, 2016). On the contrary, Interpretivism emphasizes unpredictable reality, each experience represents reality and identifies individual experiences as different realities, therefore tries to explain the investigated phenomenon through the differences between individuals in their role as social actors (Creswell, 2009; Saunders & Lewis, 2012). Interpretivism studies social phenomena in their natural environment where individuals produce their own sense of social reality, hence understanding the phenomena through the experiences and perception of those participating in it. Interpretive studies mostly employ qualitative research methods to investigate and describe social realities. Pragmatism emphasizes the importance of research questions and objectives as the determinant of research philosophy. It supports mixed-method approaches, and it originates where the researcher may employ several methods that reflect his values (Saunders & Lewis, 2012). realism philosophy a view the truth is universal and independent of human knowledge and perception, thus reality is independent of the mind. Realism links to the scientific inquiry approach. It emphasizes that what our senses recognize as reality is the truth (Saunders & Lewis, 2012). Research of which is based on a structured observable and measurable data to answer the research questions adopt a positivism research paradigm.

Regarding the literature review, IT innovation adoption studies have broadly revealed the relationship between adoption factors at different levels of individual, organizational, and environmental with IT adoption attitude and behaviour. An empirically supported variance in the determinantal power of these factors was observable in literature. However, understanding the degree to which these relationships have a measurable impact on the adoption decision has significantly contributed to the development of the business environment and IT science. This research poses research questions in which interrelate and guide the research used methods. It seeks to assess the knowledge in which based on factual measurement of the variables and investigate the theoretical facts underlying the introduced framework. Accordingly, this research is an exploratory study that adopts a positivism research paradigm.

Research Approaches. Business research is defined as “an organized, systematic, data-based, critical, objective, inquiry or investigation into a specific problem” (Sekaran & Bougie, 2016). The research approach can be into three types, qualitative, quantitative, and mixed. Qualitative research investigates social problems from individuals perceived meaning, data are gathered in the participant's setting in the form of words through interviews, open-ended questions in a questionnaire, observation, and other means. In the Quantitative approach, the researcher produces understanding and interpretations in a flexible structure (Creswell, 2009). Numbered data are collected and the relationships among the research variables are objectively tested through statistical analysis procedures. The data are gathered through structured questions which isolated from bias or judgment (Creswell, 2009). Mixed methods research combines both qualitative and quantitative to address questions in which cat be answered by a single approach, it aims to collect, analyze, and mixing both quantitative and qualitative data to strengthen the research result than solely one method (Sekaran & Bougie, 2016). This research aims to investigate the hypothesized relationships between a set of predefined variables with HR Leaders’ attitude toward the adoption of AI in HRM and empirically measure their acceptance or rejection. This research aims to produce an objective and statistical analysis of the phenomena being researched to test the hypothetical generalizations of the theory while maintaining independence. Therefore, this research quantitative methodology.

Inductive and Deductive Reasoning. In social research, both inductive and deductive can be applied to investigate the research question. The deductive research approach refers to the set of reasoning used to test a theoretical proposition using a research strategy which precisely designed to perform this test. It involves several steps among which, define the problem statement, generates research questions, operationalizes questions, develops hypotheses, defines measures, data collection and analysis. the Interpretation is by confirming the general theory or modifying it in the light of the findings. On contrary, the Inductive research approach involves analyzing collected data to develop a general theory that explains the research question. Inductive starts from specific observations to broader conclusions (Saunders & Lewis, 2012; Sekaran & Bougie, 2016). Generally, deductive reasoning supports causal and structured research settings and more often used in quantitative studies, while inductive reasoning is more often used in exploratory and qualitative studies (Sekaran & Bougie, 2016). Therefore, this research employs the deductive reasoning method.

4.2. RESEARCH DESIGN

Sekaran & Bougie, (2016) defines research design as "a blueprint or plan for the collection, measurement, and analysis of data, created to answer your research questions" and involves deciding on research design elements from a set of alternatives for which significantly impact research quality and effectiveness. Among these elements are research strategy, researcher interference, study setting, unit of analysis, and time horizon. Moreover, defining the data collection method, sample design, tools of measurement (Sekaran & Bougie, 2016). Research design draws a guidance frame that direct the data collection and analysis process and ensure that implemented research procedures are best to explain and fulfil the research objectives. This section will highlight this research decision-making process regards the research design elements and their implementations.

4.2.1. Research strategy

The research **strategy** is a predefined research plan that aims to attain the research objectives and provide a scientific answer for questions in research, therefore, deciding on research strategy is very much connected to the research objectives, research questions, the researcher perceptions about the aptness of strategy, and research practical aspects (Sekaran & Bougie, 2016). This study aims to empirically test the defined hypotheses; hence a conceptual framework has been developed to present the proposed research hypotheses between the study variables. Hypotheses are logical speculation of a relationship between two or more variables and they offer a better understanding of the phenomenon being investigated in the form of testable statements (Sekaran & Bougie, 2016). Testing the research hypothesized correlation provides confirmative answers to the peculated relationships among research variables. Therefore, this study employs a survey strategy to attain the research objectives of delineating the significance of a predefined set of predictors and their impact on HR leaders' attitude towards the adoption of AI in HRM and test the inner constructs hypothesized relationships.

4.2.2. Interference and Study Setting.

The extent of interference by the researcher can be classified into three-level, minimal, moderate, and excessive interference; while the study setting can be classified into two categories contrived or non-contrived setting (Sekaran & Bougie, 2016). This study is a correlation study for which delineate research variables, collects the data, and analyze them to produce finding with minimal interference by the researcher in a non-contrived field setting.

4.2.3. Unit of Analysis, and Time Horizon.

The unit of analysis is defined as the "level of aggregation of the data collected during the subsequent data analysis stage" and can be classified into six categories, individual, dyads, groups, divisions, industry, and countries unit of analysis (Sekaran & Bougie, 2016). Besides, the time horizon can be classified into cross-sectional versus longitudinal studies. Cross-sectional studies are also called one-shot, where data are gathered at once over a specific period unit (days, weeks, months), while longitudinal studies the research phenomena are examined at more than one point of time such as before and after a specific change in environment or external factor influence (Sekaran & Bougie, 2016). To examine the hypotheses relationship, this research data is collected from HR leaders at one point, therefore, this research analysis unit is individual with a cross-sectional time horizon.

4.2.4. Data Collection Methods, Sampling and Research Instruments

This research is constructed based on two sources of data, primary and secondary. Secondary data are those for which were collected for some other purpose than this research. Secondary data is considered a variable source that has several advantages among which: easy access and analysis, low cost, timesaving, and unobtrusive method, provide a large volume of related data in different forms and methods, offer comprehensive better understanding for the research, and provides comparative contextual background about the research project (Saunders & Lewis, 2012). The secondary data were mostly in form of written documentary literature (e.g., reports, journals article, and books, annual reports) that related to the research area. The secondary data were sourced in both digital and hard format using key search terms in which designed by the researcher and from screening the related literature. Although it is not sufficient to meet the specific requirements of this research problem and objectives, thus, the secondary data have had the following important contribution:

- Provide a better comprehensive understanding of IT innovation adoption research.
- Define the research variable through comparatively review their importance in the literature.
- Observe facts and patterns of analysis.
- Discover research gaps and shortages.
- Determine the research methodology and inputs for the data collection methods.

Primary data is defined as “data collected specifically for the research project being undertaken” (Saunders & Lewis, 2012). It can be collected through different methods such as interviews, observations, and administering questionnaires. The questionnaire is a preformulated written set of questions to which participants answer using closely defined alternatives (Sekaran & Bougie, 2016). A questionnaire is commonly used to collect a large volume of quantitative data and can be administered personally, electronically, or through mailed (Sekaran & Bougie, 2016) however each method has advantages and disadvantages (see Figure 10).

This research primary data were collected using an online questionnaire. Besides the above-mentioned advantages, several practical and methodological reasons have influenced the selection in favour of online survey, among which:

- Covid-19 pandemic forced lock-down and emergency procedures,
- The online survey allowed the further explanation of AI deployment in HRM to ensure respondents are updated with recent trends.
- Easier distribution, responses processing, and coding.

4.2.5. Instrument Development

The questionnaire development process has several steps for which provides frame guidance to ensure its effectiveness and that collected data are appropriate to test our hypotheses.

Mode of data collection	Advantages	Disadvantages
Personally administered questionnaires	Can establish rapport and motivate respondent. Doubts can be clarified. Less expensive when administered to groups of respondents. Almost 100% response rate ensured. Anonymity of respondent is high.	Explanations may introduce a bias. Take time and effort.
Mail questionnaires	Anonymity is high. Wide geographic regions can be reached. Token gifts can be enclosed to seek compliance. Respondent can take more time to respond at convenience. Can be administered electronically, if desired.	Response rate is almost always low. A 30% rate is quite acceptable. Cannot clarify questions. Follow-up procedures for nonresponses are necessary.
Electronic questionnaires	Easy to administer. Can reach globally. Very inexpensive. Fast delivery. Respondents can answer at their convenience like the mail questionnaire. Automatic processing of answers.	Computer literacy is a must. Sampling issues. High non-response. Not always possible to generalize findings. Respondent must be willing to complete the survey. People find invitations via email rude and offensive; emails are deleted or people complain.

Figure 10: Advantages and Disadvantages of Questionnaire Types
Source (Sekaran & Bougie, 2016)

In this research context, firstly the questionnaire has been validated against the principles of wording the questions. (Sekaran & Bougie, 2016) defined five principles of wording:

1. The appropriateness of the content of the questions.
2. How questions are worded and the level of sophistication of the language used
3. The type and form of questions asked.
4. The sequencing of the questions.
5. The personal data sought from the respondents.

The appropriateness of survey questions was carefully considered so that the variables are adequately measured each based on the nature of the variable (subjective, objective) and the intended type of data in which to be collected. Questions were drawn from literature and previous studies related to IT innovation adoption, IT trust and HR roles within the organization where validity and reliability have been established (see Table 1), hence, questions items were slightly modified and reworded to fit this research context. The questionnaire used the English language, stated clearly, altered in simplified language to ensure its appropriateness with respondent's level. To maintain the highly structure standardized responses and to facilitate the data analysis process, a closed-question type with predefined several alternatives is used. The questions were sequenced based on the funnel approach (Sekaran & Bougie, 2016) which promotes the smooth progress of the respondent through the items.

The questions with general nature (classification questions) such as the sample and firm characteristics information were placed at first before the questions with specific nature. Classification questions in which collects personal information about respondents were kept to the minimum level needed to meet the objectives of this research. The type of measurements was decided based on scientific methods. Measurement is defined as "the area of quantitative social science that is concerned with ascribing numbers to individuals in a meaningful way" (Salkind, 2010). It describes the used scaling techniques to measure each variable. The measurement selection plays a major role in assessing the reliability and validity of the used measures, and it is dependent on the type of data in which meant to be collected (Sekaran & Bougie, 2016). Although measurements are distinctive from statistics, measurement methods are grounded on statistical application. Four types of measurement are recognized in social science research nominal, ordinal, interval, and ratio. Ordinals are categorical data that are put into a specific order, nominal data are categorical with no obvious rank order, interval data are "measured numerically so that the numerical difference between two values can be stated, but not the relative difference", while ratios "are numerical data whose values are measured numerically so that both the numerical and the relative difference between two values can be stated" (Saunders & Lewis, 2012).

The types of measurement scales used in this research were based on the nature of the question. Table 3 summarizes the instrument content, measures, and sources. In the first part of the questionnaire which covers sample and company characteristics, the nominal scale was utilized. Within this measurement type, the numbers assigned to the items have no quantitative meaning beyond indicating their presence or absence and cannot perform any arithmetic operations (Hair et al., 2014). The first part of the questioner included five questions that collect information about respondents' country of employment, age, academic level, experience, and job title. The consequent parts of the questioner adopted a five-point rating scale (Likert scale) where each object is scaled independently. The Likert scale allows subsequently classify responses in terms of the level of agreement or disagreement and distinguish the variation between responses. They are easily analyzed and administered, especially with online e-mail questionaries (Hair et al., 2014). The second part consisted of 19 questions that assess the innovation characteristics factors. The third part consisted of 14 questions of which assess the TOE construct factors. The fourth part consisted of 15 questions of which assess the trust construct factors. The fifth part consisted of 20 questions of which assess the HR-roles construct factors. lastly, six questions were used to assess the attitude Toward Adopting AI in HRM.

Table 3: 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; T. Teo et al., 2007)
	Complexity (CPX)	4		(Martins et al., 2016; Y. S. 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; Y. S. 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; T. Teo et al., 2007)
	Competitive Pressure (CP)	4	Likert Scale (1= Strongly disagree; 5= strongly agree)	(Oliveira et al., 2014; T. Teo et al., 2007)
Total		14		
Trust	Reliability (RLA)	4	Likert Scale (1= Strongly disagree; 5= strongly agree)	(J. K. 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	(1 is very low; 5 is very high)	(Ulrich, 1997b)
	Administrative Expert (AE)	5		
	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

4.2.6. Defining Research Targeted Population

One of the significant factors of research effectiveness is population and sampling process. The population is defined as "the entire group of people, events, or things of interest that the researcher wishes to investigate" (Sekaran & Bougie, 2016). Concerning his study question and objectives (elaborated earlier in chapter one), this research aims to investigate the emerging phenomenon of utilizing AI solutions in HRM from HR Leaders' perspectives. Specifically, examine the relationship between these solutions Innovation characteristics, organizational and environmental determinants, trust, and HR roles with their attitude toward the adoption of AI in HRM. Therefore, the achievement of the research objectives is highly dependent on collected data representativeness and validity. since the study assesses HR Leaders' attitude, the targeted group of this study are those who hold a senior position and considered to be HR policymakers within the organization. The research targets HRM leaders who are involved in formulating HRM strategy and driving the department strategic orientation and HR roles within the organization, rather than lower-level HR practitioners. The rationale behind defining this target group is associated with research context, besides being policymakers, the respondents are required to be conversant about the actual IT application level at HRM within their organization, know its historical development and transformation, and understand the associated opportunities and challenges they face regarding its implementation. Besides, acknowledgeable to the emerging trends in HRIS such as AI-based solutions and able to produces a coherent judgment about its relative advantage, its compatibility with the firm values and culture, and a perception of its complexity. Further, Senior HR professionals (Managers, Directors) are more exposed to the market and competitors' practices. Previous IT adoption and implementation studies (Rand Hani Al-Dmour, 2014; C. Y. Y. Lin, 1997; Ngai & Wat, 2004; Reddick, 2009) have limited their targeted population to HR managers and Directors and argued that they should be the key informant in this type of studies (Rand Hani Al-Dmour, 2014). For instance, aiming to investigate the factors influencing the adoption of online recruitment (Parry & Wilson, 2009) targeted respondents of which were taken from a database of 8,000 HR directors and managers in the UK. Considering a specific industry or list of companies for an individual analysis unit studies such as current research, deems challenging and will limiting the population size. Generally, each company has one or two HR professionals at this senior HR leaders' level. For instance, to define a population of 1000 elements, then a similar number of companies need to be reached. Consequently, the identification and selection of the targeted population are based on the belief that it will provide data that best serve the research problem and answer the research question. This belief is descended from the researcher seven years of experience in HR senior position at a regional level within Middle East countries (Kuwait, Jordan, Iraq), related literature and previous studies, and the preliminary conducted research of which discussed in the previous sections (3.2 Relationships and Hypotheses Development). Accordingly, the defined targeted population of this study from which the sample was drawn, is HR Leaders who are a member of Middle East HR professionals' network at the LinkedIn professional network platform during the month of Jul-2020. Specific position titles were adopted as an identifier for HR leadership positions. The researcher activated a premium account to acquire access for the targeted population (see Appendix 2). The following Table 3 exhibits the set of criteria in which were employed to define the target population.

4.2.7. Sampling Frame and Sample Size

The sampling frame is "the complete list of all members of the total population." (Saunders & Lewis, 2012). For this research, the sample frame is the complete list of population elements for which represents the identified HR leaders through the mentioned filtering criteria. The total population size was 8200 in which stratified into four stratums (See Table 4, also see Appendix 2). Reflecting on (Sekaran & Bougie, 2016) generalized scientific guideline for minimum sample size table, the population size of 8000 to 9000 elements requires a minimum sample of 368, yet, Sekaran & Bougie, (2016) emphasize that a sample sizes more than 30 and less than 500 are appropriate for most research. Sekaran & Bougie, (2016) argued that among online-survey disadvantage (See Figure 10) is a high non-response rate. Therefore, the questionnaire was sent to one thousand HR Leaders drawn from the defined population stratums, a total of 389 valid responses received.

This research used a stratified random sampling method, which is defined as "probability sampling in which the sampling frame is first divided into relevant strata, Sample members are then selected at random from within each stratum" (Saunders & Lewis, 2012). Two well-known designs of the stratified random sampling method.

The proportionate stratified random sampling and disproportionate stratified random sampling. Stratified random sampling is proportionate when the representation of each stratum is proportionate to the total number of elements, while in disproportionate stratified random sampling the number of subjects is altered while keeping the sample size unchanged (Sekaran & Bougie, 2016).

Tab 4: Criteria for Defining the Targeted Population

Defining Population Characteristics	
Countries	Jordan, Kuwait, Qatar, Saudi Arabia
Connection to the researcher	1st, 2nd, and 3rd Connection (All LinkedIn Member)
Position Title	HR Manager, Senior HR Manager, HR Director, Chief Human Resources Officer (CHRO)
Profile language	English
Other Criteria	Defined employer (unambiguous employment status)

Source: Author's Construction

Also, there are two approaches to sample selection from each stratum, using either simple random sampling or systematic sampling. For this research, a systematic disproportionate stratified random sampling has been utilized (see Table 5) where the representation of each stratum is not proportionate to the total number of elements. According to (Sekaran & Bougie, 2016) disproportionate distribution might be considered in some cases more appropriate and representative than proportionate sampling design especially when one or some stratum or strata are too small or too large. Moreover, the defined aim of this research to assess the association of the defined factors with Middle east HR leaders' attitude toward the adoption of AI in HRM rather than emphasizes the difference between surveyed countries, and the similarity of chosen countries national cultural background are other reasons for selecting disproportionate sampling design.

Table 5: Disproportionate Sample Distribution

Country	Number of Elements	Proportionate Sample Size
Jordan	1100	200
Kuwait	1200	200
Qatar	1300	250
Saudi Arabia	4600	350
Total	8200	1000

Source: Author's Construction

4.2.8. Data Collection Procedure

Data were collected through an online survey. An inbox message (see Appendix 5) was sent to the participant in which included a research introduction, a motivation letter, a link to the online survey was provided and a link to a short article previously published article by the researcher on LinkedIn. The article introduces the emerging trends of AI in HRM and highlighting the importance of HR leaders exposing themselves to HRM emerging trends. Two reasons were behind including the short article link with the sent message, first is to ensure participants understanding of the research phenomenon in case they are not previously exposed to the emerging AI HRM solutions. The Second reason is driven by the researcher professional experience where HR leaders usually show higher interest to explore new HR trends which could affect the HR practices than just simply participate in random research. Therefore, the researcher first introduced the phenomenon to gain a better understanding of the research problem, then solicit their participation by providing the link for the online survey. The questionnaire was sent during the month of Jul-2020 within two days periods to ensure that no major changes have occurred to the estimated population.

4.3. DATA ANALYSIS TECHNIQUES

This section summarizes the executed analysis. Firstly, the data were extracted from the online google survey into Excel format. Data coding and data editing were performed where numbers were assigned to the participants' responses variables and were checked for illogical and inconsistent responses. For the Likert scale that ranged from "strongly disagree" to "strongly agree", a 5-point coding of 1 to 5 were assigned, respectively in the same order.

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. Moreover, the measurement scale reliability was assessed using a Cronbach's alpha value.

After establishing validity and reliability, research data appropriateness of regression analysis was examined through normality, multicollinearity, and homoscedasticity measurement. Lastly, multiple regression analysis is used to test the research hypothesized predicted relationships.

5. RESEARCH FINDINGS AND THEIR EVALUATION

This Chapter presents the findings of research quantitative data analysis cited in the previous chapter. Also, research hypotheses will be tested and subsequently presents the research results and conclusions about the underlying relationship between the research variables in which presented earlier in the research conceptual model. The analysis involves data alteration, transforming and evaluation using SPSS 25 software to produce meaningful results that answer the research questions.

5.1. DEMOGRAPHIC ANALYSIS DESCRIPTION

The research data was gathered from HR leaders within the four middle East countries through an online questionnaire and using proportionate sampling detailed earlier (see Table 4). A total of 1000 questionnaires were sent during the month of Jul-2020, a total of 389 valid responses have been received with a 38% accumulated response rate. Five demographical data in which are relevant and useful for the research objectives were collected by the questionnaire specifically, country of employment, age, academic level, HRM experience (seniority), and job title. Table 6 shows the respondents distribution within these defined categories.

The sample distributions by country of employment show that the highest responses rate from Saudi Arabia with 33% of the total sample, followed by Jordan, Kuwait, and Qatar, respectively. Saudi Arabia result is in congruence with the proportionate selected sample size of 350 sent questionnaires. However, in terms of response rate, the descending order is Jordan with 47.5%, Kuwait 42%, Saudi Arabia with 37.7%, and Qatar 31.2%. Even though Qatar had the seconded highest proportion total of 250 sent questionnaire, thus, it has the lowest response rate. This might be explained by the researcher national background and work experience in Jordan and Kuwait where respondents with managerial positions usually tend to check researchers' profile. This conclusion is based on three grounds, first is what is called similarity bias where similar characteristics affect the behaviour and perception of one person toward another, second, is my personal professional experience, third is the high rate of researcher-profile review rate on LinkedIn during Jul. and Aug. 2020.

Table 6: The Respondent's Demographical Distribution

Country	Categories	Frequency	Per cent
	Jordan	95	24.42
	Kuwait	84	21.59
	Qatar	78	20.05
	Saudi Arabia	132	33.93
	Total	**389**	**100**

Age	Categories	Frequency	Per cent
	< 25 years	3	0.77
	25-30	102	26.22
	31-40	169	43.44
	41-50	90	23.14
	> 50 years	25	6.43
	Total	**389**	**100**

Academic Level	Categories	Frequency	Per cent
	Certificate/Diploma	14	3.6
	Bachelor's degree	217	55.78
	Master's degree	131	33.68
	PhD	27	6.94
	Total	**389**	**100**

Job Seniority	Categories	Frequency	Per cent
	< 3 years	1	0.26
	3-6 years	22	5.66
	7-10 years	170	43.7
	11-14 years	103	26.48
	> 14 years	93	23.91
	Total	**389**	**100**

Job Title	Categories	Frequency	Per cent
	HR Manager	136	34.96
	Senior HR Manager	93	23.91
	HR Director	131	33.68
	CHRO	29	7.46
	Total	**389**	**100**

Source: Author's Construction

In terms of age group, the highest percentage of respondents are between 31-40 years old with a total of 169 out of 389 responses, while only 3 respondents are below 25 years old. Considered the research targets HR leaders, this is a reflective result where holding a managerial job title at a young age as much less than 25 years is rare. The same premise can apply to professional experience where only 1 respondent had less than 3 years HRM experience, while the highest percentages were 7-10 years of experience with 43% % of total responses, followed respectively by 11-14 years of experience with 26 %, more than 14 years of experience with 23 %, and 3-6 years of experience with 22%. For the respondent's academic level, the highest rate was for bachelor's degree holders with 55.7% followed respectively by the master's degree, PhDs, diploma, and non with less than a diploma.

Finally, among the defined job positions for the targeted population, the highest rate of respondents was from the HR Managers category with 34.9%, however, a close rate of 33.6% of the respondents are holding the HR director position within their organization, followed respectively by Senior HR manager and Chief Human Resources Officer.

5.2. THE FACTOR ANALYSIS, RELIABILITY AND VALIDITY FINDINGS

Factor analysis is an interdependence measure that aims to define the underlying structure among the measurement items (Hair et al., 2014). Factor analysis includes two principles, component analysis and common factor analysis. Factor analysis is used to assess the interrelationships between multiple variables and explains variables in terms of their common underlying factors (Hair et al., 2014). The aim of conducting factor analysis is to reduce a large number of commonly associated items underlie each construct into a smaller set of factors with a minimal loss of information (Hair et al., 2014). Factor analysis assesses the underlying structure for the multiple items of the research variables and illustrates the related items in which commonly adhere to a factor. By presenting an empirical estimate of the structure of the variables, factor analysis provides an objective basis for creating summated scales (Hair et al., 2014). Therefore, Factor analysis was performed to examine the underlying structure of research variables items and define the minimum number of common factors in which would satisfactorily produce the correlation between the observed variables. Accordingly, factor analysis is employed in this research to discover the main patterns of factors that underlie each of the research constructs namely TOE, HR role, trust, innovation characteristics, and as an intermediate step for further regression and association analysis.

A principal component analysis (PCA) was conducted on the 74 items of independent research constructs to examine the underlying structure for the research variables items. Thus, at first, the sample appropriateness and Adequacy for factor analysis have been analyzed through assessing the items, Size, *Kaiser Meyer Olkin (KMO),* Communalities, *and* total variance explained.

5.2.1. Sample Size

The common general rule in defining the sample size appropriate for factor analysis. Is that at least 10–15 participants per variable, however, some researchers recommended between 5 and 10 participants per variable up to a total of 300. Tabachnick & Fidell, (2007) argued that at least 300 cases for factor analysis are comforting (Field, 2009). However, the universal agreement that a sample size below 50 is inappropriate for factor analysis.

5.2.2. *Kaiser Meyer Olkin (KMO)*

KMO measures the sampling adequacy by assessing the relationship between the variable represented by the ratio of the squared correlation between items to the squared partial correlation between items. It ranges between 0 and 1 and the more the values close to 0 indicates that the sum of partial correlations is large compared to the sum of correlations and the inappropriateness of factor analysis (Field, 2009). A value close to 1 indicates the compactness of correlations patterns, hence, factor analysis would yield distinct and reliable factors. while the recommends accepting values greater than 0.5 as barely, values between 0.5 and 0.7 are mediocre, values between 0.7 and 0.8 are good, values between 0.8 and 0.9 are great and values above 0.9 are superb (Field, 2009). The Kaiser–Meyer–Olkin (KMO) measure for the research instrument items (see Table 7) verified the sampling adequacy for the factor analysis, KMO measure of sampling adequacy for this data set of variables was = .888. Bartlett's test of sphericity χ^2 (2701) = 24452, $p < .001$, indicated that correlations between items were sufficiently large for PCA.

Table 7: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.888
Bartlett's Test of Sphericity	Approx. Chi-Square	24452.866
	Df	2701
	Sig.	0.000

Source: Author's Calculation

5.2.3. Communality Measures

Communality measures the proportion of variance explained by the extracted factors, in other words, the total amount of variance an original item shares with all other research items (Hair et al., 2014). Assessing communality assessment helps to detect any variables that are not adequately accounted for by the factor solution, hence not meeting the acceptable levels of explanation. The value of the communality is a useful indicator for assessing the variance in a particular variable that is accounted for by the factor solution. Higher communalities indicate that a large amount of the variance in a variable has been extracted by the factor solution. Small communalities show that a substantial portion of the variable's variance is not accounted for by the factors. The applied thumbs rule is that factor solution should explain at least half of each item's variance, therefore, using the recommended 0.4 threshold guideline all variables with communalities less than .40 is identified as not having sufficient explanation (Field, 2009). Appendix (1) shows extracted Communality and initial loadings for the research items. The results showed that all the communalities have met the 40% threshold. The communality extraction ranged between 89.4% for ATT6, and 48.7% scored for AE2.

5.2.4. Total Variance Explained

An initial analysis was run to obtain eigenvalues for each component in the data. The eigenvalue is the square sum of a factor and it represents the range of variance yielded by each factor (Hair et al., 2014). The results of the PCA have yield 15 factors that can be extracted from the various research constructs in which had eigenvalues over Kaiser's criterion of 1 and in combination explained 72.57% of the variance (see Table 8). However, considering the Interpretability principal which indicates that smaller factors are retained only if it comprises a sufficient substantial meaning. Moreover, given the convergence of the scree plot of which was slightly ambiguous and showed some inflexions, therefore, ten factors are retained for further analysis.

Table 8: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	17.952	24.260	24.260	17.952	24.260	24.260	16.486
2	9.132	12.341	36.601	9.132	12.341	36.601	8.057
3	4.659	6.296	42.897	4.659	6.296	42.897	9.356
4	3.884	5.249	48.146	3.884	5.249	48.146	5.192
5	2.613	3.531	51.677	2.613	3.531	51.677	5.607
6	2.187	2.955	54.632	2.187	2.955	54.632	6.373
7	1.861	2.515	57.147	1.861	2.515	57.147	3.158
8	1.751	2.366	59.513	1.751	2.366	59.513	4.961
9	1.655	2.237	61.750	1.655	2.237	61.750	4.485
10	1.630	2.203	63.953	1.630	2.203	63.953	4.393
11	1.522	2.057	66.011	1.522	2.057	66.011	3.578
12	1.408	1.903	67.914	1.408	1.903	67.914	2.077
13	1.288	1.740	69.654	1.288	1.740	69.654	2.872

14	1.111	1.502	71.155	1.111	1.502	71.155	2.135
15	1.051	1.421	72.576	1.051	1.421	72.576	1.883
16	0.990	1.338	73.915				
....							
74	0.032	0.043	100.000				
Extraction Method: Principal Component Analysis.							
a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.							

Source: Author's Calculations

5.2.5. Items Loading

Loadings represent the index of the size and direction of the association of the research variables with a factor or discriminant function (Hair et al., 2014). PCA was conducted, rotation Method: Promax oblique rotation Kaiser Normalization. According to (Hair et al., 2014) "The researcher should always consider applying a nonorthogonal rotation method and assess its comparability to the orthogonal results". Moreover, oblique rotation is recommended when an expected correlation between the perceptual dimensions exists (Hair et al., 2014). For instance, for the HR roles constructs the fact that HRM usually has the four defined roles at the same time, hence with different densities. For instance, a strategic partner role has a high correlation with the change agent role where the HR department with strategic involvement would mostly obtain a high change agent role. The same concept can be applied to some of the other research constructs. Since Promax oblique rotation permits factors to correlate, it is believed that the oblique rotation method will generate a better result. When an oblique rotation is applied, it yields two matrices, the pattern matrix, and the structure matrix. The pattern matrix includes the loadings on each factor and is comparable to the factor matrix that of orthogonal rotation (Field, 2009). The structure matrix considers the relationship between factors. However, most researchers consider the pattern matrix preferable for interpretative purposes because it reveals information about the unique contribution of a variable to a factor (Field, 2009). Appendix (1) shows the factors pattern matrix extracted based on ten factors. Variables with loading equal or above 0.3 are considered significant and a threshold 0.4 as a minimum loading value (Hair et al., 2014).

Several items are shown to have a gross-loading problem or did not meet the 0.4 threshold. Eight items had to be removed specifically (CRD2, TC4, AE1, AE2, AE3, AE4, AE5, EC5). It is noticeable 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. TC4, CRD2 had significant gross loading, while EC5 did not meet the 0.4 loading threshold.

5.3. THE INTERPRETATION OF THE FINAL FACTOR ANALYSIS

The below sections present the main patterns of factors underlying each of the research constructs.

5.3.1. Factor Analysis: Innovation Characteristics Construct

The **Innovation Characteristics** construct consists of five variables namely: Relative Advantage (RA), Profitability (PRO), Complexity (CPX), Security Concerns (SEC), and Compatibility (COM). **Innovation Characteristics** construct was measured using a total of 18 items. The (KMO) measures for the innovation characteristics construct items (see Table 9) verified the sampling adequacy for the factor analysis, the KMO measure of sampling adequacy scored = .862. Bartlett's test of sphericity χ^2 (171) = 4757, $p < .001$, indicated that correlations between items were high enough for PCA.

Table 9. KMO and Bartlett's Test for Innovation Characteristics Construct

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.862
Bartlett's Test of Sphericity	Approx. Chi-Square	4757.413
	df	171
	Sig.	0.000

Source: Author's Calculations

Factors were extracted using PCA with Promax rotation with Kaiser normalization at eigenvalue >1. Table 10 shows the results of the total variance explained which indicate that four factors are extracted for innovation characteristics construct variables. The first factor has 6.54 Sums of Squared Loadings and 6.07 after rotation, it accounts for 34.42% of variance extraction and can be labelled as the "Relative Advantage" factor. The second factor has 3.39 Sums of Squared Loadings and 3.75 after rotation, it accounts for 17.87% of variance extraction and can be labelled as the "Compatibility" factor. The third factor has 2.18 Sums of Squared Loadings and 3.30 after rotation, it accounts for 11.47% of variance extraction and can be labelled as the "Security Concerns" factor. The fourth factor has 1.15 Sums of Squared Loadings and 3.22 after rotation, it accounts for 6.04% of variance extraction and can be labelled as the "Complexity" factor. The cumulative total of variance extracted is 69.79% which is considered acceptable to proceed with statistical analysis.

Total 10: Variance Explained for Innovation Characteristics Construct

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadingsa
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	6.54	34.42	34.42	6.54	34.42	34.42	6.07
2	3.39	17.87	52.29	3.39	17.87	52.29	3.75
3	2.18	11.47	63.76	2.18	11.47	63.76	3.30
4	1.15	6.04	69.79	1.15	6.04	69.79	3.22
Extraction Method: Principal Component Analysis. Rotation Method: Promax with Kaiser Normalization.							
a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.							

Source: Author's Calculations

For a construct comprehensive overview Table 11 illustrates the list of items, instrument question, their loading pattern matrix, and communality scores. For the first factor, Loadings ranging from 0.89 for PRO2 to 0.77 for RA5 all exceeding the threshold of 0.4, while communalities ranged between 76% to 63% all exceeding the minimum defined threshold of 0.4. The second-factor Loadings ranging from 0.90 for COM3 to 0.76 for COM2 all exceeding the threshold of 0.4, while communalities ranged between 78% to 62% both exceeding the minimum defined threshold of 0.4. The third-factor Loadings ranging from 0.89 for SEC2 to 0.80 for SEC1 all exceeding the threshold of 0.4, while communalities ranged between 83% to 77% all exceeding the minimum defined threshold of 0.4. The fourth-factor Loadings ranging from 0.86 for CPX4 to 0.62 for CPX3 all exceeding the threshold of 0.4, while communalities ranged between 64% to 57% all exceeding the minimum defined threshold of 0.4.

Table 11: Pattern Matrix and Communalities for Innovation Characteristics Construct

Item Code	Loading				**Extraction**
	Factor 1	Factor 2	Factor 3	Factor 4	
COM1		0.85			0.72
COM2		0.76			0.62
COM3		0.90			0.78
COM4		0.84			0.72
CPX1				0.72	0.54
CPX2				0.78	0.64
CPX3				0.62	0.59
CPX4				0.86	0.63
PRO1	0.85				0.70
PRO2	0.89				0.75
PRO3	0.86				0.69
RA1	0.84				0.76
RA2	0.85				0.73

RA3	0.80				0.71
RA4	0.79				0.63
RA5	0.77				0.63
SEC1			0.80		0.77
SEC2			0.94		0.83
SEC3			0.92		0.83
Eigenvalue	6.54	3.39	2.18	1.15	Cumulative %69.79
% of Variance	34.42	17.87	11.47	6.04	
Extraction Method: Principal Component Analysis. Rotation Method: Promax with Kaiser Normalization.					

Source: Author's Calculation

5.3.2. Factor Analysis: Technology Trust Construct

The technology trust construct consists of four variables namely: Reliability (RLA), Credibility (CRD), Technical Competence (TC), and Trust (TRS). The technology trust construct was measured using a total of 13 items. The (KMO) measures for the trust construct items (see Table 12) verified the sampling adequacy for the factor analysis, the KMO measure of sampling adequacy scored = .846. Bartlett's test of sphericity χ^2 (78) = 4726, p < .001, indicated that correlations between items were sufficiently high enough for PCA.

Factors were extracted using PCA with Promax rotation with Kaiser normalization at eigenvalue >1. Table 13 shows the results of the total variance explained which indicate that only one factor is extracted from trust construct variables in which can be labelled as the "Trust" factor since it has the higher loading values. The extracted factor accounts for 8.19 Eigenvalue and 62.9% of the cumulative total of variance extracted which is considered acceptable to proceed with statistical analysis.

Table 12: KMO and Bartlett's Test for Technology Trust Construct

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.846
Bartlett's Test of Sphericity	Approx. Chi-Square	4726.7
	df	78
	Sig.	0.000

Source: Author's Calculation

Table 13: Total variance explained for Trust Construct

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Eigenvalue	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	8.19	62.98	62.98	8.19	62.98	62.98
2	0.96	7.41	70.39			
Extraction Method: Principal Component Analysis.						

Source: Author's Calculation

For a construct comprehensive overview, Table 14 illustrates the list of items, instrument question, their loading component matrix, and communality scores. Loadings ranging from 0.82 for TRS3 to 0.75 for TC3, all exceeding the threshold of 0.4, while Communalities ranged between 68% for to 56% all exceeding the minimum assigned threshold of 0.4.

Table 14: Component Matrix and Communalities for Technology Trust Construct

Code	Item	Loading Factor 1	**Extraction**
CRD1	AI would operate in is a truthful and non-biased manner	0.81	0.65
CRD3	AI would operate in HRM best interest	0.81	0.65
CRD4	AI is safe, adequate and error-free	0.79	0.63
RLA1	AI-based systems work in a consistent and predictable manner	0.75	0.57
RLA2	I can forecast in advance how AI will work for a specific HRM task	0.82	0.67
RLA3	AI-based systems will consistently perform under a variety of circumstance	0.78	0.60
RLA4	As an HRM solution, AI is very predictable	0.77	0.59
TC1	AI solutions are competent and effective in processing HRM tasks	0.80	0.64
TC2	AI is capable and proficient in autonomously processing HRM tasks	0.79	0.63
TC3	AI has the features required to perform HRM work activities	0.75	0.56
TRS1	I can depend and rely on AI HRM solutions	0.79	0.63
TRS2	AI is straight, trustworthy, and legitimate	0.82	0.67
TRS3	I trust AI-based solutions in HRM	0.83	0.68
Eigenvalue		8.188	Cumulative %62.341
% of Variance		62.983	
Extraction Method: Principal Component Analysis.			

Source: Author’s Calculation

5.3.3. Factor Analysis: Technological- Organization-Environment (TOE) Construct.

The TOE construct consists of four variables namely: Competitive Pressure (CP), Firm Size (SZE), Top Management Support (TMS), and Technological Readiness (TC). TOE construct was measured using a total of 14 items. The (KMO) measures for the TOE construct items (see Table 15) verified the sampling adequacy for the factor analysis, the KMO measure of sampling adequacy scored = .801. Bartlett’s test of sphericity χ^2 (91) = 2602, p < .001, indicated that correlations between items were sufficiently high enough for PCA.

Table 15: KMO and Bartlett's Test for TOE Construct

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.8013
Bartlett's Test of Sphericity	Approx. Chi-Square	2602.9
	df	91
	Sig.	0.000

Source: Author’s Calculation

Factors were extracted using PCA with Promax rotation with Kaiser normalization at eigenvalue >1. Table 16 shows the results of the total variance explained which indicate that four factors are extracted for TOE construct variables. The first factor has 4.45 Sums of Squared Loadings and 3.83 after rotation, it accounts for 32.54% of variance extraction and can be labelled as the "Top Management Support" factor. The second factor has 2.23 Sums of Squared Loadings and 3.08 after rotation, it accounts for 15.91% of variance extraction and can be labelled as the "Competitive Pressure" factor. The third factor has 1.63 Sums of Squared Loadings and 3.06 after rotation, it accounts for 11.65% of variance extraction and can be labelled as the "Technological Readiness" factor. The fourth factor has 1.57 Sums of Squared Loadings and 1.64 after rotation, it accounts for 11.22% of variance extraction and can be labelled as the "Firm Size" factor. The cumulative total of variance extracted is 71.32% which is considered acceptable to proceed with statistical analysis.

For a construct comprehensive overview Table 17 illustrates the list of items, instrument question, their loading pattern matrix, and communality scores. For the first factor, Loadings ranging from 0.94 for TMS2 to 0.86 for TMS2 all exceeding the threshold of 0.4, while communalities ranged between 86% to 74% all exceeding the minimum defined threshold of 0.4. The second-factor Loadings ranging from 0.91 for CP4 to 0.73 for CP2 all exceeding the threshold of 0.4, while communalities ranged between 78% to 64% both exceeding the minimum defined threshold of 0.4. The third-factor Loadings ranging from 0.84 for TR3 to 0.69 for TR2 all exceeding the threshold of 0.4, while communalities ranged between 68% to 45% all exceeding the minimum defined threshold of 0.4. The fourth-factor Loadings ranging from 0.90 for SZE2 to 0.89 for SZE1 all exceeding the threshold of 0.4, while communalities ranged between 81% to 80% all exceeding the minimum defined threshold of 0.4.

Table 16: Total Variance Explained for TOE Construct

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	4.56	32.54	32.54	4.56	32.54	32.54	3.83
2	2.23	15.91	48.45	2.23	15.91	48.45	3.08
3	1.63	11.65	60.09	1.63	11.65	60.09	3.06
4	1.57	11.22	71.32	1.57	11.22	71.32	1.64
Extraction Method: Principal Component Analysis. Rotation Method: Promax with Kaiser Normalization.							
a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.							

Source: Author's Calculation

Table 17: Pattern Matrix and Communalities for TOE Construct

Item Code	Loadings				Extraction
	Factor 1	Factor 2	Factor 3	Factor 4	
CP1		0.86			0.73
CP2		0.73			0.64
CP3		0.77			0.65
CP4		0.91			0.78
SZE1				0.90	0.81
SZE2				0.89	0.80
TMS1	0.94				0.83
TMS2	0.86				0.74
TMS3	0.88				0.86
TMS4	0.89				0.80
TR1			0.75		0.64
TR2			0.69		0.45
TR3			0.84		0.68
TR4			0.75		0.60
Eigenvalue	4.56	2.23	1.63	1.57	Cumulative %71.32
% of Variance	32.54	15.91	11.65	11.22	
Extraction Method: Principal Component Analysis. Rotation Method: Promax with Kaiser Normalization.					
a. Rotation converged in 4 iterations.					

Source: Author's Calculation

5.3.4. Factor Analysis: HR-Roles Construct

The HR-Roles construct consists of three variables (note: one variable Administrative Expert was deleted) namely: Strategic Partner (SP), Employees Champion (EC), and Change Agent (CA). HR-Roles construct was measured using a total of 14 items. The (KMO) measures for the HR-Roles construct items (see Table 18) verified the sampling adequacy for the factor analysis, the KMO measure of sampling adequacy scored = .904. Bartlett's test of sphericity χ^2 (91) = 3368, p < .001, indicated that correlations between items were sufficiently high enough for PCA.

Table 18: KMO and Bartlett's Test for HR Roles Construct

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.904
Bartlett's Test of Sphericity	Approx. Chi-Square	3368.7
	df	91
	Sig.	0.000

Source: Author's Calculation

Factors were extracted using PCA with Promax rotation with Kaiser normalization at eigenvalue >1. Table 19 shows the results of the total variance explained which indicate that three factors are extracted for HR-Roles construct variables. The first factor has 7.00 Sums of Squared Loadings and 5.57 after rotation, it accounts for 50.02% of variance extraction and can be labelled as "Strategic Partner" factor. The second factor has 1.68 Sums of Squared Loadings and 5.82 after rotation, it accounts for 11.99% of variance extraction and can be labelled as the "Change Agent" factor. The third factor has 1.01 Sums of Squared Loadings and 4.61 after rotation, it accounts for 7.20% of variance extraction and can be labelled as the "Employees Champion" factor. The cumulative total of variance extracted is 69.22% which is considered acceptable to proceed with statistical analysis.

Table 19: Total Variance Explained for HR Roles Construct

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	7.00	50.02	50.0227	7.00	50.02	50.0227	5.5736
2	1.68	11.99	62.0171	1.68	11.99	62.0171	5.8223
3	1.01	7.202	69.2186	1.01	7.202	69.2186	4.6132
Extraction Method: Principal Component Analysis.							
a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.							

Source: Author's Calculation

For a construct comprehensive overview Table 20 illustrates the list of items, instrument question, their loading pattern matrix, and communality scores. For the first factor, Loadings ranging from 0.93 for SP3 to 0.66 for SP1 all exceeding the threshold of 0.4, while communalities ranged between 83% to 57% all exceeding the minimum defined threshold of 0.4. The second-factor Loadings ranging from 0.87 for CA2 to 0.67 for CA3 all exceeding the threshold of 0.4, while communalities ranged between 70% to 64% both exceeding the minimum defined threshold of 0.4. The third-factor Loadings ranging from 0.87 for EC1 to 0.76 for EC2 all exceeding the threshold of 0.4, while communalities ranged between 73% to 60% all exceeding the minimum defined threshold of 0.4.

Table 20: Pattern Matrix and Communalities for HR-Roles Construct

Item Code	Loading			**Extraction**
	Factor 1	Factor 2	Factor 3	
CA1		0.78		0.64
CA2		0.87		0.69
CA3		0.67		0.65
CA4		0.77		0.70
CA5		0.86		0.69
EC1			0.87	0.69

EC2			0.76	0.60
EC3			0.86	0.73
EC4			0.79	0.73
SP1	0.66			0.57
SP2	0.77			0.73
SP3	0.81			0.67
SP4	0.93			0.83
SP5	0.93			0.77
Eigenvalue	7.00	1.68	1.01	Cumulative %69.22
% of Variance	50.02	11.99	7.20	
Extraction Method: Principal Component Analysis. Rotation Method: Promax with Kaiser Normalization.				
a. Rotation converged in 4 iterations.				

Source: Author's Calculation

5.4. RELIABILITY MEASURE

Reliability is the assessment of scale measures to determines its homogeneity and the degree of consistency between multiple measurements of a variable (Hair et al., 2014). In other words, assessing if the questionnaire item would consistently reflect the constructs in which it measures. Also, A strong reliability of the research instrument supports the generalization of the research findings. Several measures are applied by researchers to prove the instrument reliability; hence, two main measures are most frequently used. First is the correlation of each item to the summated scale score and the inter-items correlation where the suggest the acceptable result is that correlation exceed 0.5 and 0.30 respectively (Hair et al., 2014). The second method is the most widely used in assessing the consistency of the entire scale using Cronbach's alpha. Cronbach's alpha is a measure of the extent to which participants respond consistently on all the items that represent a scale or a variable. The formula of the Cronbach's alpha is (Field, 2009):

$$\alpha = \frac{N.\bar{c}}{\bar{v}+(N-1).\bar{c}}$$

The Cronbach's alpha measure of reliability ranges from 0 to 1, with values of 0.60 to 0.70 considered the lower limit of acceptability (Hair et al., 2014). Table 21 shows the reliabilities measures (Cronbach's alpha) for the research variables. the result reveals that the alpha value ranged descendingly between the highest value of 0.944 for the Attitude Toward AI adoption (ATT) variable and the lowest value is 0.695 for the Trust (TRS) variable, however, it has a marginal value of 7 and above the 0.6 acceptable thresholds. The overall alpha value. All other variables have exceeded the threshold of 0.7. The research overall scale is 0.921. Based on these results of which indicates that scales deemed good internal consistency, the reliability of the research instrument is assumed and confirmed.

Table 21: Reliability Estimations of Instrument Measures

Construct	Variables	Cronbach's Alpha (α)
Innovation Characteristics	Compatibility (COM)	0.859
	Complexity (CPX)	0.763
	Profitability (PRO)	0.894
	Relative Advantage (RA)	0.908
	Security Concerns (SC)	0.881
Technological Organizational Environmental (TOE)	Competitive Pressure (CP)	0.839
	Technological Readiness (TR)	0.759
	Top Management Support (TMS)	0.917
	Firm Size	0.732
Technology Trust	Reliability (RLA)	0.845
	Credibility (CRD)	0.818
	Technical Competence (TC)	0.778
	Trust (TRS)	0.695
HR Roles	Strategic Partner (SP)	0.895
	Employee Champion (EC)	0.848
	Change Agent (CA)	0.877
Attitude Toward AI adoption	Attitude (ATT)	0.944
The Overall α for the research scale		0.921

Source: Author's Calculation

Previous analysis has demonstrated the validity and reliability of the research instrument. Measurements with statistically significant high loadings on a factor indicate the converge on a common point, hence high convergent validity. Besides, convergent validity is supported by demonstrating the high reliabilities of scales in measuring the constructs. Convergent validity would not be met when low-reliability levels are revealed. All research variables Cronbach's alpha measures have met the acceptable level of Cronbach's alpha measure, hence supporting Convergent validity.

5.5. APPROPRIATENESS OF REGRESSION ANALYSIS

Before conducting a regression analysis to test the research hypothesized predicted relationships. Several assumptions are advised to be inspected considered to examine the appropriateness of regression analysis on the collected data. The following section will examine those statistical considerations of normality, Multicollinearity, and homoscedasticity (Hair et al., 2014).

5.5.1. Distribution Normality

Normality is the degree to which the sample data distribution corresponds to a normal distribution, the standard of statistical methods is If the variation from the normal distribution is large then all resulting statistical tests are invalid because normality is required to use the F and t statistics. (Hair et al., 2014). While the test of normality is strongly recommended for small-sized samples e.g. (fewer than 30), Thus, according to (Hair et al., 2014), researchers should always check both the graphical plots and any statistical tests to assess the actual degree of departure from normality. Also, assessing the level of significance for the differences from a normal distribution is necessary for checking the data appropriateness for specific analysis methods.

To test the research data normality first is a graphical P-P plot and the values of skewness and kurtosis analyses of normality are produced. Examining the P-P plot reveals (see Appendix 3) the absence of significant deviation of the dots from the probability line and the alignment of research variables residuals with the line indicates the normal distribution of data. In addition to examining the normal probability plot, a statistical test of normality has been assessed using Kurtosis and skewness values. Kurtosis refers to the "peakedness" or "flatness" of the height of distribution when compared with the normal distribution, while skewness describes the balance of the distribution if its centred and symmetrical with about the same shape on both sides or its skew positively to the left or negatively to the right (Hair et al., 2014). Table 22 present the Skewness and kurtosis Z value for the research variables. Applying the ±2.58 critical value role (Hair et al., 2014), results fit within the range hence, indicates normal distribution.

5.5.2. Multicollinearity

Multicollinearity is the "Extent to which a variable can be explained by the other variables in the analysis" (Hair et al., 2014). Multicollinearity occurs when a strong correlation exists between two or more predictors in a regression model. The premise behind assessing multicollinearity is that a perfect linear relationship between two or more of the predictors should not exist between two or more predictors in a regression relationship, therefore, variables should not correlate too high (Field, 2009). The ultimate collinearity or multicollinearity happens in a singularity situation where the independent variable is perfectly predicted at 1.0 level by another independent variable, however, it is very rare to happen.

Table 22: Statistical Test of Normality

Construct	N	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Firm Size	389	5	3.1	1.049	-0.257	-0.759
Compatibility	389	5	3.56	0.784	-0.899	0.929
Relative Advantage	389	5	4.01	0.705	-1.051	1.589
Complexity	389	5	3.25	0.667	0.111	-0.017
Profitability	389	5	3.99	0.725	-0.523	0.039
Security Concerns	389	5	3.31	0.84	0.063	-0.542
Top Management Support	389	5	3.67	0.919	-0.577	-0.125
Technological Readiness	389	5	3.65	0.73	-0.696	0.407
Competitive Pressure	389	5	3.33	0.771	-0.086	-0.459
Reliability	389	5	4.00	0.636	-0.733	0.778
Credibility	389	5	3.97	0.666	-0.734	0.6
Technical Competence	389	5	3.91	0.661	-0.759	0.813
Trust	389	5	3.95	0.744	-1.078	1.606
Strategic Partner	389	5	3.39	0.882	-0.156	-0.804
Employee Champion	389	5	2.96	0.889	0.241	-0.435
Change Agent	389	5	3.20	0.888	-0.016	-0.606
Attitude Toward Adoption	389	5	3.89	0.831	-0.864	0.034

Source: Author's Calculation

Multicollinearity measure is important because the extent of high association between independent variables reduces its predictive power of the dependent variable. Therefore, maximizing the prediction of a given number of independent variables, independent variables should have low multicollinearity with each other (Hair et al., 2014). The simplest method in measuring the collinearity is to assess the correlation matrix for independent variables and check for high correlations above 0.8 and 0.9 are considered high collinearity indicators (Hair et al., 2014). However, collinearity may occur because of the multicollinearity combined effect of more than one independent variables. Researchers are recommended to first diagnose multicollinearity before proceeding with regression analysis. Therefore, to effectively assess multicollinearity needs to assess the extent to which each independent variable is explained by the set of other independent variables (Hair et al., 2014). The most commonly used methods to assess multicollinearity is to extract the tolerance and variance inflation factor (VIF). Tolerance is the degree of variability of an independent variable not explained by the other independent variables, while VIF is the inverse of the tolerance value. The recommended common cutoff threshold for the tolerance value is .10, which corresponds to a VIF value of 10 (Hair et al., 2014).

A nonparametric correlation analysis has been performed between the main constructs variables with Attitude (ATT) as the dependent variable. The result showed no correlation exceeding the 0.8 collinearity indicator which supports the absence of multicollinearity. (see Appendix 4) shows the main research constructs collinearity statistics and correlation Coefficient. The highest is between strategic partner HR role and change agent HR role with r =0.534, and relative advantage and trust with r =0.527, respectively. However, did not exceed the 0.8 multicollinearity indicator threshold. Moreover, presents the test of tolerance and variance inflation factor (VIF) for the research constructs. All variables are above the tolerance cutoff threshold of 0.1 and below the VIF threshold of 10. Results ranged from the lowest tolerance of 0.4 with 2.5 VIF for the change agent variable to the highest tolerance of 0.94 with 1.06 VIF for the firm size variable. These results prove the absence of multicollinearity.

Multicollinearity for Relative Advantage and Trust prediction Relationships: A nonparametric correlation between the innovation characteristics sub-construct prediction relationships of Relative Advantage (RA), specifically Profitability (PRO) and Security Concerns (SC) as independent variables and Relative Advantage (RA) a dependent variable. The result (Table 23) showed no correlation exceeding the 0.8 collinearity indicator which supports the absence of multicollinearity. One moderate above 0.5 correlation have been found between PRO and RA with r =0.682, thus, did not exceed the 0.8 multicollinearity indicator threshold. The test of tolerance and variance inflation factor (VIF) for the RA prediction relationship variables are above the tolerance cutoff threshold of 0.1 and below the VIF threshold of 10. These results prove the absence of multicollinearity.

A nonparametric correlation between the of Trust (TRS) construct prediction relationships, specifically Credibility (CRD), Technological Competence (TC), and Reliability (RLA) as independent variables and Trust (TRS) a dependent variable. The result (Table 24) showed no correlation exceeding the 0.8 collinearity indicator which supports the absence of multicollinearity. Slightly high correlations have been found between the construct variables ranged from the highest between CRD and TC r =0.736 to r =0.664 between RLA and TRS with r =0.736. however, did not exceed the 0.8 multicollinearity indicator threshold. The test of tolerance and variance inflation factor (VIF) for the TRS prediction relationship variables are above the tolerance cutoff threshold of 0.1 and below the VIF threshold of 10. These results prove the absence of multicollinearity.

Table 23: Relative advantage Collinearity Statistics and Correlation Coefficient

Variables	Tolerance	VIF	PRO	SC	RA
Profitability	0.992	1.009	1.000		
Security Concerns	0.992	1.009	-0.071	1.000	
Relative Advantage	dependent		.682**	-.116**	1.000
**. Correlation is significant at the 0.01 level (2-tailed).					

Source: Author's Calculation

Table 24: Trust Collinearity Statistics and Correlation Coefficient

Variables	Tolerance	VIF	CRD	TC	RLA
Credibility	0.20	4.94	1.000		
Technical Competence	0.23	4.29	.726**	1.000	
Reliability	0.22	4.55	.736**	.695**	1.000
Trust	dependent		.643**	.725**	.664**
**. Correlation is significant at the 0.01 level (2-tailed).					

Source: Author's Calculation

5.5.3. Homoscedasticity

The third assumption of regression is homoscedasticity. It refers to the assumption that the dependent variable displays an equal level of variance across the range of the predictors. Homoscedasticity is desirable because it indicates that the dependent variable is being explained in a wider variance range of independent values rather than unequal dispersion across values of the independent variable for which indicates heteroscedasticity (Hair et al., 2014). The best commonly used method to assess homoscedasticity is the graphical examination of the prediction relationship scatterplot. The similarity of the plots of the data points along the regression line without any clear pattern of increasing or decreasing residuals distribution. Therefore, deviations from an equal dispersion can be shown by such shapes as cone and funnel shape where the distribution is more intense at one side than the other, or diamonds shapes with more concentration at the centre which may indicate heteroscedasticity. The scatterplot of regression standardized predicted value and standardized residual for the research hypothesized relationships have been examined separately to assess the homoscedasticity of values. Figure 11 exhibits the generated scatterplot in the following order:

(A) The scatterplot of regression standardized predicted value with standardized residual for the main constructs variables with Attitude (ATT) as the predicted dependent variable and 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) as predictors variables.

(B) The scatterplot of regression standardized predicted value with standardized residual for the innovation characteristics sub-construct variables with Relative Advantage (RA) as the predicted dependent variable and Profitability (PRO) and Security Concerns (SC) as predictors variables.

(C) The scatterplot of regression standardized predicted value with standardized residual for the Trust construct variables with Trust (TRS) as the predicted dependent variable and Credibility (CRD), Technical Competence (TC), and Reliability (RLA) as predictors variables.

Assessing the produced regression scatterplot, relationships (A) and (B) did not exhibit a clear indication of heteroscedasticity, therefore homoscedasticity is assumed. However, a suspected funnel or onside concentration is suspected for the (C) relationship for the Trust construct, therefore, it is decided to consider the difference between a regression and correlation analysis if existed for this construct relationships.

Summarizing the regression appropriateness Analysis, in this section the three suggested assumptions of regression, namely: normality, multicollinearity, and homoscedasticity have been checked for before proceeding with regression analysis. The result demonstrated the normal distribution of values, the absence of serious multicollinearity and heteroscedasticity for predictor variables. A suspected exception in term of heteroscedasticity for the Trust construct relationship which will be managed by considering the correlation jointly with regression analysis and compare results.

5.6. REGRESSION ANALYSIS: TESTING RESEARCH HYPOTHESES

In this section, the research constructs factors and associated variables hypothesized predictive relationships are analyzed. At first, the two construct-level relationships (Relative advantage, Trust) are examined, then the main predictive relationships in which presented within the research conceptual framework (see Figure 5) between the research constructs and HR leaders' attitude toward the adoption of AI in HRM.

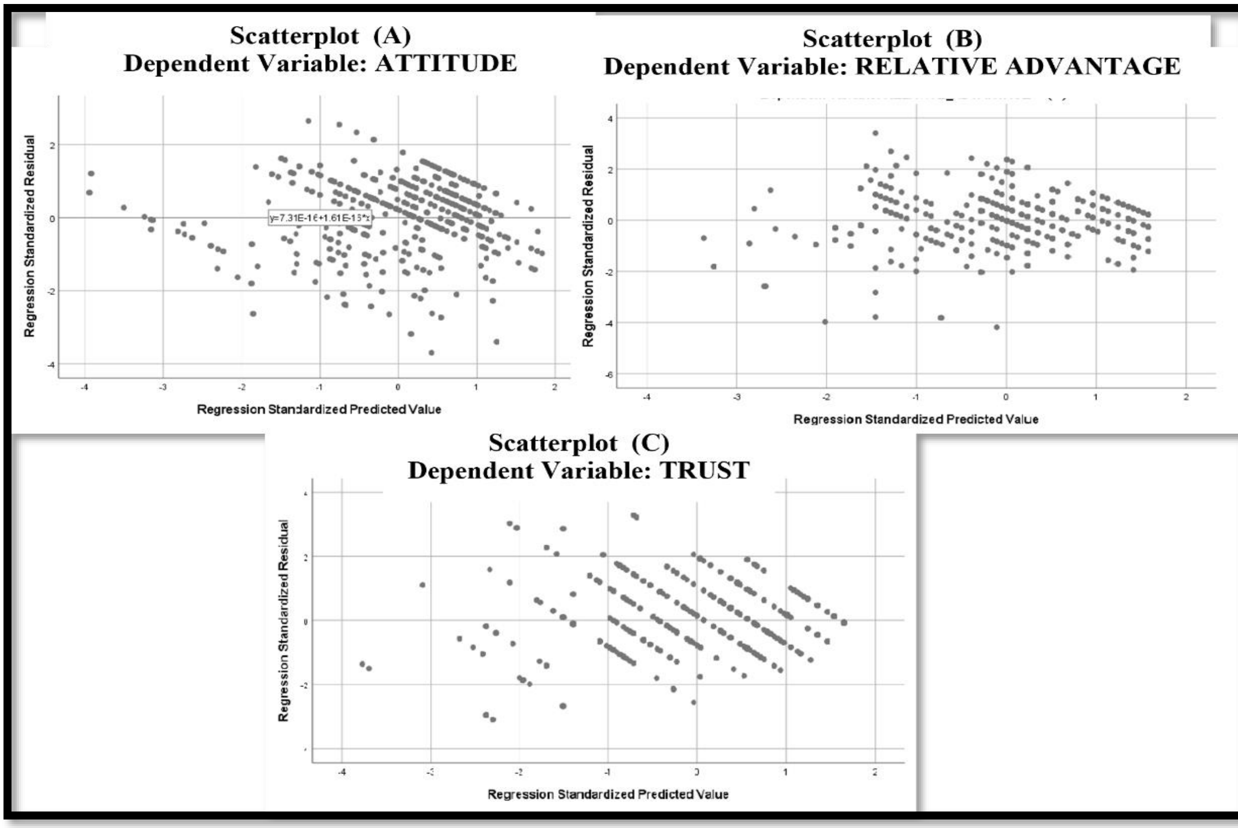

Figure 11: Scatterplot
Source: Author's Construction

To achieve this purpose, multiple regression analysis is used. Multiple regression analysis is a statistical technique that examines the relationship between a single predicted variable and several independent predictors. The aim is to utilize the known values of independent variables to predict a single dependent to answer the research questions. In regression analysis, each independent variables is weighted to maximize its prediction power (Hair et al., 2014). According to (Hair et al., 2014) regression is a useful dependence technique in which widely used to solve important research problems in business decision making research and applied in either general or specific problems. It is the groundwork for business forecasting models at the micro firm-level to macro-econometric level. (Hair et al., 2014). Besides, literature has reflected the wide and intense use of regression in technology adoption research. Consequently, this research will rely on the regression analysis method to answer the posed research question and attain the declared objectives.

The multiple regression analysis is carried out at two levels, at the inner-construct level and the general main research constructs level. First, hypothesized relationships for Innovation characteristics construct. Secondly, the hypothesized relationships for the Trust construct are examined. Finally, the hypothesized relationships between the main research conceptual framework construct's independent variables and the dependent variable Attitude toward Adoption (ATT) are tested.

5.6.1. 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). Figure 12 exhibits the result where both predictor variables, Profitability and Security Concerns are significant predictors of the Relative advantage. While profitability appears to be significantly positively related to relative advantage, the security concern has a significant negative relation with relative advantage.

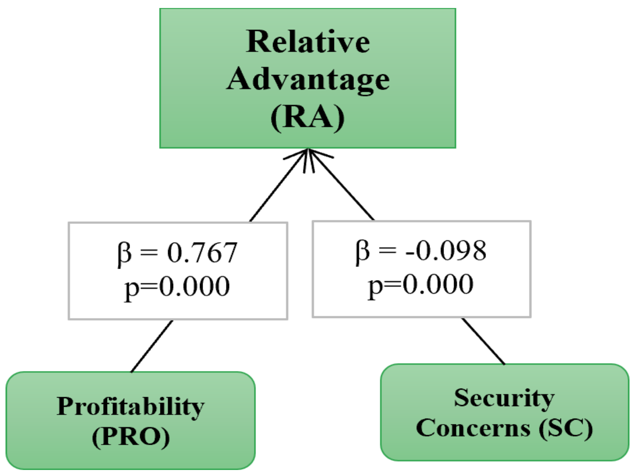

Figure 12: Result of RA Prediction relationship
Source: Author's Construction

Moreover, Table. 25 shows the results of the stepwise regression analysis which shows that the adjusted square of both predictors is .650 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 0.630.

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								

Source: Author's Calculation

Further, the ANOVA test (Table 26) shows an F ratio of 361.646, at significance p <0.000 which indicate the overall model fit.

Table 26: Predictors of Relative Advantage ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	125.831	2	62.915	361.646	.000b
	Residual	67.152	386	.174		
	Total	192.983	388			
a. Dependent Variable: RELATIVE_ADVANTAGE						
b. Predictors: (Constant), PROFITABILITY, SECURITY_CONCERNS						

Source: Author's Calculation

5.6.2. 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). Figure 13 exhibits the result where all 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 27) 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.

This result is compatible with correlation analysis (see Table 28) where all predictors variables had a strong correlation with Trust at the p=0.000 level. Further, the ANOVA test (Table 28) shows an *F* ratio equal to 421.733, at significance p <0.000 which indicate the overall model fit.

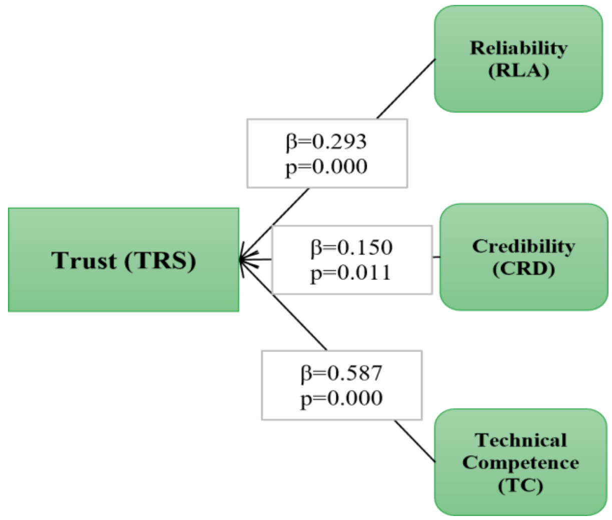

Figure 13: Result of Trust Prediction relationship
Source: Author's Construction

Table. 27: 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 Calculation

Table 28: Predictors of Trust ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	164.818	3	54.939	421.733	.000[b]
	Residual	50.154	385	.130		
	Total	214.972	388			
a. Dependent Variable: TRUST						
b. Predictors: (Constant), TECHNICAL_COMPETENCE, RELIABILITY, CREDIBILITY						

Source: Author's Calculation

5.6.3. 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 29 shows the results of the multiple regression analysis which indicates that among the predictor variables, only three are significant predictors 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 0.505 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 30).

Table 29: 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

The overall adjusted square for the predictors is 0.458 which indicates that 45.8% of the variance in the Attitude (ATT) 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 firm Size (SZE) predictor demonstrated a strong relationship with the dependent variable ATT with β=0.52, however not significant at p=0.05 level.

Table 30: 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

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. Further, the ANOVA test (Table 31) shows the *F* ratio equal to 30.688, at significance p <0.000 which indicate the overall model fit.

Table 31: Predictors of ATTITUDE ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	129.670	11	11.788	30.688	.000[b]
	Residual	144.818	377	0.384		
	Total	274.487	388			
a. Dependent Variable: ATTITUDE						
b. Predictors: (Constant), EC, CP, SZE, CPX, TMS, TRS, TR, SP, COM, RA, CA						

Source: Author's Calculation

The Research hypotheses results are summarized in below Table 32.

Table 32: 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

5.7. FINDINGS AND DISCUSSION

The purpose of this research is to broaden the current knowledge about technology contribution in HRM by investigating the phenomenon of emerging AI and machine learning HR solutions from HR leaders' perspective A conceptual framework has been developed to guide this investigation. The framework defined a specific set of factors in which were perceived as important determinants in explaining the attitude toward the adoption of AI in HRM. The research constructs importance is based on a broad exploration and review of HRIS adoption and development literature. The key predictors were categorized within the following four main constructs that predict HR leaders' attitude toward adopting AI in HRM:

1. The first construct is Innovation Characteristics with five variables: profitability, security concerns, relative advantage, compatibility, and complexity; With Profitability, security concerns as a predictor of relative advantage.

2. The second construct is Technology Trust with four variables: credibility, reliability and technical competence as a predictor of HR leaders trust in AI, and Trust variable as a predictor of their attitude toward adopting AI in HRM.
3. The third construct is TOE factors with four variables: firm size, top management support, technological readiness, and competitive pressure as predictors of HR leaders' attitude toward adopting AI in HRM.
4. The fourth construct is HR-roles with four variables: strategic partner, administrative expert, employee champion, and change agent as predictors of HR leaders' attitude toward adopting AI in HRM. However, the prediction relationship was not tested, and it was excluded for validity reasons.

The empirical investigation for hypothesized framework relationships has provided valuable input for answering the research questions, explaining the prediction power of these factors and their importance.

5.7.1. General Mean Indicators

To facilitate the analysis of the mean value result for the research factors, a three-level scale will be created using the following principle:

$$\text{Category length} = \frac{\text{(Maximum weight 5 – lowest weight 1)}}{\text{Number of levels (3)}} = \frac{4}{3} = 1.33$$

- 1 – less than or equal 2.33 LOW
- > 2.33 – less than or equal 3.66 Moderate
- > 3.66 – less than or equal 5 High

From a general perspective, analyzing the mean for responses reveals that the research indicators had a higher mean than the median of 2.5 (See Table 21). This leads to several conclusions regarding the research sample perception of each measured variable within each construct. For instance, among the mean values for innovation characteristic construct, the higher responses mean value of 4.01 was for relative advantage factor of which indicates that HR leaders highly perceive an advantage added by AI to the HRM function. Similarly, the profitability factor had a mean value of 3.99 which also indicate respondents are more highly positive about the gained profitability from AI tools. Yet, the responses mean value for complexity and security concerns (3.25, 3.31 respectively) reveals that the average respondents believe that understanding how AI works is a moderately complex process and has a security risk.

Considering responses mean values for the Trust construct, results of the three trust factor predictors (reliability, credibility, technological competence) had a high mean value. The reliability factor had a mean value of 4.00 which indicates that on average, HR leaders tend to perceive AI applications in HRM as reliable and predictable tools. The credibility factor had a mean value of 3.97 in which also considered a positive attitude toward AI credibility. Among the three predictors of trust, technological competence had the lowest mean value of 3.91, thus, it also expresses that on average, HR leaders have an opinion that AI is a highly competent tool in handling HRM tasks. Finally, the trust factor has a mean value of 3.95 reveals that generally, HR leaders have a high trust feeling toward the AI-based HRM.

For TOE and HR-roles constructs, responses mean value also provide some insights concerning the respondents' organizations characteristics, the level of technological readiness, the emphasized HR roles within the organization, and their perception about competitive pressure. Among the TOE predictors of HR leaders' attitude toward AI, top management support had the highest mean value of 3.67 out of 5, this indicates that HR leaders' perception about top management support of seeking new technological advancement is slightly high. The technological readiness factor had a mean value of 3.65 which indicates the respondent's perception about their organization technological readiness to utilize AI in HRM is moderate. The lowest mean value of 3.33 for the TOE construct was associated with competitive readiness, this indicates that the HR leaders' perception about the pressure of which resulted from competitor's adoption of AI is moderate. From the HR roles perspective, examining the mean value provides an indicator of the average level of emphasis of which each HR role has on the respondents' organizations. The result revealed that the highest mean value of 3.69 was associated with administrative experts HR role, which means that the HR department of respondents has a high administrative expert role within the organization. The second and third empathized HR roles are the strategic partner and change agents with a mean value of 3.39, 3.2 respectively. This value indicates the HR department of respondents has a moderate strategic partner and change agents roles within the organization. Lastly, the lowest mean value of HR roles is 2.96 for the employee champion role which also considered moderate.

The mean value of 3.89 for the research dependent variable the Attitude toward AI adoption has indicated that on average, HR leaders have a high positive attitude toward utilizing AI techniques within HRM tasks.

5.7.1. Innovation Characteristics Prediction of Attitude Toward Adoption

The first hypothesized relationships within the innovation characteristics is an effort to discover the factors of which determine the relative advantage of AI in HRM. This research has identified profitability and security concerns as predictors of AI innovations relative advantage. Profitability reflects the perceived gained financial benefit of innovation in terms of profitability. The result showed profitability as a significant predictor of relative advantage. This result indicates that HR leaders' perception that the benefits of adopting AI HR tools are greater than the costs, helps to avoid unnecessary cost, and increases the cost-saving of the company is a positive predictor in which explains the relative advantage. This result is consistent with studies that have found profitability and cost-savings to be a strong driver of IT innovation relative advantage and adoption (Benlian & Hess, 2011; Martins et al., 2016; Oliveira et al., 2014). Also, the results confirm the hypothesized negative association between HR leaders concerns about AI potential security and privacy risks with their perception of AI relative advantage. This result confirms the previous findings (Benlian & Hess, 2011) about security concerns prediction of adoption. Reflecting this result on AI tools in HRM (e.g., chatbots, ATS), it is noticeable that these solutions are consistent with contemporary trends of IT innovation features in which increasingly relies on SaaS (on-demand software) and cloud-based services. This feature distinguishes AI HR applications from the conventional HRIS by exempting the organization from IT infrastructure, installation, and data storage cost which provides a higher degree of freedom in terms of selection and implementation decisions. However, it is argued that these IT service increases the data security and privacy concerns, hence impact the degree of its advantageous and the results of this study support this argument.

The second hypothesized relationships within this construct is an effort to investigate the prediction between innovation characteristics variables (relative advantage, complexity, compatibility) with the research main dependent variable attitude toward the adoption of AI in HRM. The results provided empirical evidence that supports the proclaimed significance of innovation characteristics as a predictor of IT innovations diffusion (Rogers, 2003). Consistent with previous IT innovation diffusion and adoption research (Al-Dmour Rand, Masa'deh Ra'ed, 2017; Alam et al., 2016; L. F. Chen & Chien, 2011; A. Lin & Chen, 2012; Low et al., 2011; Oliveira et al., 2014; Parry & Wilson, 2009;

Premkumar & Roberts, 1999; Puklavec et al., 2018; T. Teo et al., 2007; Yang et al., 2015), relative advantage showed to be a strong positive predictor HR leaders attitude toward the adoption of AI in HRM. The relative advantage factor represents the perceived usefulness of AI in terms of productivity, efficiency, role in improving the quality of decision making by eliminating human mistakes and bias. Besides, providing more opportunities and gaining competitive pressure. The empirical results of this research signify the importance of HR leaders' perceptions about the extent of these AI advantages in shaping their attitude toward it. Besides, this result confirms the previously introduced results for the perceived usefulness (PU) factor within the technology acceptance model (TAM) and performance expectancy in the unified theory of acceptance and use of technology (UTAUT) model. The second innovation characteristic factor is complexity. Complexity was hypothesized to be a negative predictor of attitude toward AI. The results have supported the hypothesized relationship and showed complexity as a strong negative predictor at p=0.000. Complexity represents their perception about the extent of how difficult to understand and use AI. This result confirms previous studies (Al-Dmour Rand, Masa'deh Ra'ed, 2017; Rand H. Al-Dmour et al., 2016; Martins et al., 2016; Palos-Sanchez et al., 2017; Rouhani et al., 2018). This implies that HR leaders' beliefs about the level of complexity in implementing AI, the difficulty level in learning how it works, the complexity of its integration process with current practices, and the complexity of its development, are all significant factors that drive their attitude toward it. However, it is important to cite that the degree of perceived complexity is much connected to the respondent's awareness and knowledge of AI-based software features and their technical IT skills in general.

Compatibility is the third innovation characteristic factor of which hypothesized to predict the attitude toward the adoption of AI in HRM. Compatibility reflected the degree to which AI applications are perceived as consistent with the existing values, policies, experiences, and needs of HRM. Contrary to the hypothesized relationship, compatibility did not show to be a significant predictor of HR leaders' attitude toward AI. In other words, HR leaders' perception about the extent to which AI application is compatible with current human resources practices, organization culture and values, company work style and the IT policies is not a significant predictor of their attitude toward it. This result contradicts several previous and other IT innovation studies (Grandon & Pearson, 2004; A. Lin & Chen, 2012; Taylor & Todd, 1995). Also, his result contradicts studies (Al-Dmour Rand, Masa'deh Ra'ed, 2017; T. Teo et al., 2007) of which showed that compatibility proclaimed to be a significant factor in HRIS and e-HR adoption. However, among of other innovation characteristics (relative advantage, complexity), compatibility has the most argument of about its significance where it showed no significance on some other IT innovation research such as cloud computing and SaaS (Low et al., 2011; Martins et al., 2016; Oliveira et al., 2014). This research result shows a negative association, thus, not significant at the p=.05 level. Martins et al., (2016) study in assessing the diffusion of Software as a Service (SaaS) have also found a non-significance negative association and argues that this could reflect a lack of concern regarding compatibility in the firm's value chain activities. In other words, what could explain this result is the trending transformation of IT services toward cloud computing and SaaS could reduce the pressure of normative compatibility as a determinant of adoption. While this result raises a question about the significance of compatibility as a predictor of adoption, however, generalizing the result and assuming that the more advancement in IT innovations the less importance of compatibility factor requires further investigation especially in AI and machine learning context.

5.7.2. Technology Trust Prediction of Attitude Toward Adoption

From the trust perspective, this research had two main objectives. The first is to investigate the determinants of trust in AI in processing HR tasks, to do so, three hypnotized relationships between reliability, credibility, and technological competence as predictors factors of HR leaders trust in AI. The second objective is to investigate the association between trust and HR leaders' attitude toward the adoption of AI in HRM.

Confirming the research hypothesis, reliability was found to be a significant predictor of trust at p=0.000. This result entails that HR leaders' perception about the extent to which AI applications are predictable and consistent, and their ability to forecast its working method for the specific HR tasks are significantly positively affecting their attitude toward it. Similarly, the credibility factor was found to be a significant factor in predicting AI trust. This result reveals that the HR leaders' perception about the AI truthfulness, integrity, adequacy, accuracy, and non-bias proceeding of HR tasks is a significant positive predictor of their attitude toward its adoption. The third trust predictor is technological competence, this factor assessed the HR leaders' perception of AI applications competency and effectiveness in autonomously processing HRM tasks such as applicants sourcing and screening. Moreover, their perception of its capability to produce the desired outputs and suitability for HRM work activities. The result has confirmed the research hypothesis that technological competence is a significant positive predictor of HR leaders trust in AI.

To achieve the second objective for this construct, the relationship between the trust factor as a predictor of attitude toward adoption have been examined. The result supports the hypothesized positive significant influences of trust on attitude toward adoption at p=0.000. This result indicates that the extent to which HR leaders believe in AI as a straight, trustworthy, dependable, and legitimate method of processing HRM tasks, and the level of their trust in it, significantly drive their attitude toward its adoption. The research findings regarding technology trust construct are consistent with previous studies (Casey & Wilson-Evered, 2012; J. K. Choi & Ji, 2015; El-Khatib et al., 2003; El-Masri & Tarhini, 2017; Gefen, 2002; Hasan et al., 2012; Hmoud & Várallyai, 2020; G. Kim et al., 2009; Xin Luo et al., 2010; Mcknight & Chervany, 2002; Parasuraman et al., 2008; Yusoff et al., 2015) of which tackled the phenomenon of IT innovation trust.

5.7.3. TOE Prediction of Attitude Toward Adoption

The third construct of which this research framework included is the TOE factors. This construct aimed to investigate the influential relationship between a predefined set of TOE predictors with HR leaders' attitude toward the adoption of AI in HRM. A total of four determinates were selected to represents this construct, the technological aspect is represented with technological readiness factor, the organizational with top management support and firm size factors, and the environmental is represented with competitive pressure factor. The predictor's selection was based on inputs from HRIS and modern IT innovations literature where these predictors have received researchers' attention and repetitively shown their significance in predicting IT innovations adoption. The top management support factor assessed the association between the HR leaders' perception about: 1. Management attitude towards technological advancement. 2. The extent to which management would likely invest to fund AI in HRM. 3. Management level of understanding of AI benefits. 4. Management proactive efforts in sourcing new IT innovations, with HR leaders' attitude toward the adoption of AI in HRM. Although the empirical results showed a positive association between TMS and attitude toward AI (p=0.076), it is not significant at the p=0.05 level and therefore rejecting the hypothesis. However, considering the discovered relationship, this result still could be to a certain degree confirming to the previous HRIS and IT innovations studies (Ahmer, 2013; Rand H. Al-Dmour et al., 2016; Bhatiasevi & Naglis, 2018; Low et al., 2011; Ngai & Wat, 2004; Premkumar & Ramamurthy, 1995; Ramdani et al., 2009; S. Sun et al., 2018) in which supported the significance of TMS predictor.

Firm size was determent using two criteria, the company headcount and annual review. Like TMS, the regression result showed a positive relationship (p=0.052), thus not significant at the p=0.05 level. this result brings the firm size as a significant determinant of Its adoption argument back into the debate. Although early IT HRIS and IT adoption studies (Ball, 2001; Florkowski & Olivas-Luján, 2006; Hausdorf & Duncan, 2004; Strohmeier & Kabst, 2009; T. Teo et al., 2007) have found firm size as a significant predictor, (Kimberly, 1981) argued that effects of size may depend on the nature of the innovation. From the literature, it is noticeable that contemporary emerging IT innovations such as SaaS Researches (Palos-Sanchez et al., 2017; Thu Ha et al., 2020; van de Weerd et al., 2016) and big data (S. Sun et al., 2018) studies found no significant association. This research result adds another empirical evidence to these previous findings in terms of the adoption of AI in HRM. This decreasing importance of firm size can be explained by the same premise which used to justify its importance. In other words, the firm size was considered an important determinant based on two theoretical assumptions. First is that big firms have increased resources and flexibility to invest in IT infrastructure, while the second assumption is that big firms have a higher work volume in which could justify the investment in IT innovation. Theoretically, if we isolate these two assumptions, the firm size will lose its significance. The observer of the emerging of IT innovations such as analytical big data tools, chatbots, and AI-based solutions would notice that it is shifting toward on-demand service providing (SaaS), in other words, the cost is associated with actual use without initial installation fixed cost. This method of acquiring IT services eliminates the two assumptions in which firm size importance originated upon where companies could use the IT services per actual need. However, this assumption is much connected with respondents' level of understanding of the IT innovation in question and its adoption phase, therefore, it requires further verification from similar IT adoption research.

Technological readiness factor aimed to assess the relationship between respondents' perceptions about the role of IT systems in their company, IT technical skills and knowledge, and IT resources on their attitude toward the adoption of AI in HRM. This research hypothesized that there is no significant influence of technological readiness on the attitude. The result supported the hypothesized assumption and showed that technological readiness is not a predictor of AI adoption in HRM. This result confirms other studies (Hmoud & Várallyai, 2020; Low et al., 2011; Y. Wu et al., 2013), which argued that technological readiness is losing its importance as a determinant of for the emerging IT innovations. Similar to the firm size argument, the noticeable trend in IT within the new era of 4.0 and AI is moving toward cloud computing and on-demand services. In other words, the advancement in the hardware industry, pacifically storage capacity, opened the door for software service providers to reduce user's technical dues by transforming them into web-based services. For instance, the majority of international recruitment services providers who apply AI-based techniques in their search engine or instantaneous customer communication provides these services through the purchased-license method. Although configuration and data entry is needed, hence in terms of hardware, no substantial investment is required. This trend reduces the technological cost and lessens the significance of technical compatibility as a factor in proclaiming the service.

In this research, the Environmental factors are confined in assessing the competitive pressure as a predictor of attitude toward the adoption of AI in HRM. It was hypothesized that competitive pressure constitutes a significant influence on the attitude of HR leaders. However, the result has rejected this hypothesis and showed the absence of a significant relationship at the p=0.05 level. This result reveals that HR leaders' perception of the existing competitor's usage of AI in HRM, the extent of pressure from competitors, the need to utilize AI in HRM to maintain its competitiveness, and the degree to which the company keeps tracking of newly used IT by competitors, is not a significant predictor of their attitude toward the adoption of AI in HRM. Between the two sides of previously offered empirical evidence, this research result contradicts with (H. F. Lin & Lin, 2008; Low et al., 2011; Oliveira & Martins, 2010; To & Ngai, 2006) studies which have found a significant relationship between competitive pressure and IT innovation adoption. However, support previous studies in which showed that competitive pressure lacks empirical evidence to be a significant factor in influencing IT adoption, such as HRIS (Al-Dmour Rand, Masa'deh Ra'ed, 2017; T. Teo et al., 2007), cloud computing (Oliveira et al., 2014) and other IT innovations (Ramdani et al., 2009; T. S. H. Teo et al., 2009; Y. S. Wang et al., 2016). This result can be explained from two perspectives, the first is the argument that specific industry characteristics may intervene by altering the strength of competitive pressure where the competition level varies within the different industries. For instance, competition intensity is associated with the number of competitors within the same market. Also, for IT innovations adoption, high-tech industries of which relies heavily on IT (e.g., telecommunication, autonomous vehicles, Virtual reality, and artificial intelligence) poses higher pressure than other industries. Therefore, perhaps considering isolating industries as a mediation factor between competitive pressure and IT adoption would show a different result. The second consideration in which could explain this result is the diffusion phase. It is argued that the more advanced is the adoption phase the more competitive associated. In other words, the early adoption phase poses less significant pressure than the advance adoption phases where the IT innovation value have been verified and widely accepted. Despite its progressive emergence and deployment during the last five years, AI usage in HRM still considered in its early diffusion phases.

5.7.4. HR Roles Prediction of Attitude Toward Adoption

The last construct within the research framework is HR roles factors. As explained within the research objectives, the aim was to provide a further understanding of the influence of the emphasized HR roles within the organization on adopting HRIS, specifically AI in HR in this research context. Four HR roles were defined based on (Ulrich, 1997b)s HR-Roles model which categorized it into a strategic partner, administrative expert, employee champion and change agent. The HR roles were examined by way of collecting information about the main contribution of the HR department to the organization, how the company sees the HR function, the objectives of the HR department within the organization, the processes and tasks in which the HR department is performing, and the used measures to evaluate the HR department effectiveness. Based on previous theoretical sense and previous empirical, it was hypothesized that strategic partner, administrative expert, and change agent roles positively influence HR leaders' attitude toward the adoption of AI in HRM. Employees champion was perceived as the opponent of technology involvement in HRM, hence, poses a negative influence on attitude toward adoption. The administrative expert role was excluded for not meeting the validity standards. Against expectation, the research results have shown no significant association of any of the remaining three HR roles with the attitude toward AI adoption in HRM, thus rejecting the three hypotheses. This result contradicts previous HRIS research (Panayotopoulou et al., 2007; Voermans & Van Veldhoven, 2007; Yusoff et al., 2015) in which have investigated the HR roles factor and found at least one association among these HR roles with HRIS adoption. This result raises a question about the effectiveness of using the perceived actual HR roles emphasis rather than the preferred role. The reason behind this question is that HR practitioners understanding of HR roles within the organization is relative and bounded by the organization business style and direction. Further, their perception of the HR roles interferes in their responses.

6. CONCLUSIONS AND RECOMMENDATIONS

The Research findings have been thoroughly presented within the previous chapter (chapter 5) outlining the research data validity, reliability, and the result of the research hypothesized relationships between the research variables. This chapter will present the research conclusions and recommendations based on the previously defined research objectives and provides answers for the research question based on the acquired results.

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 aispresented in the below Figure 14, accepted research hypotheses are distinguished with colours.

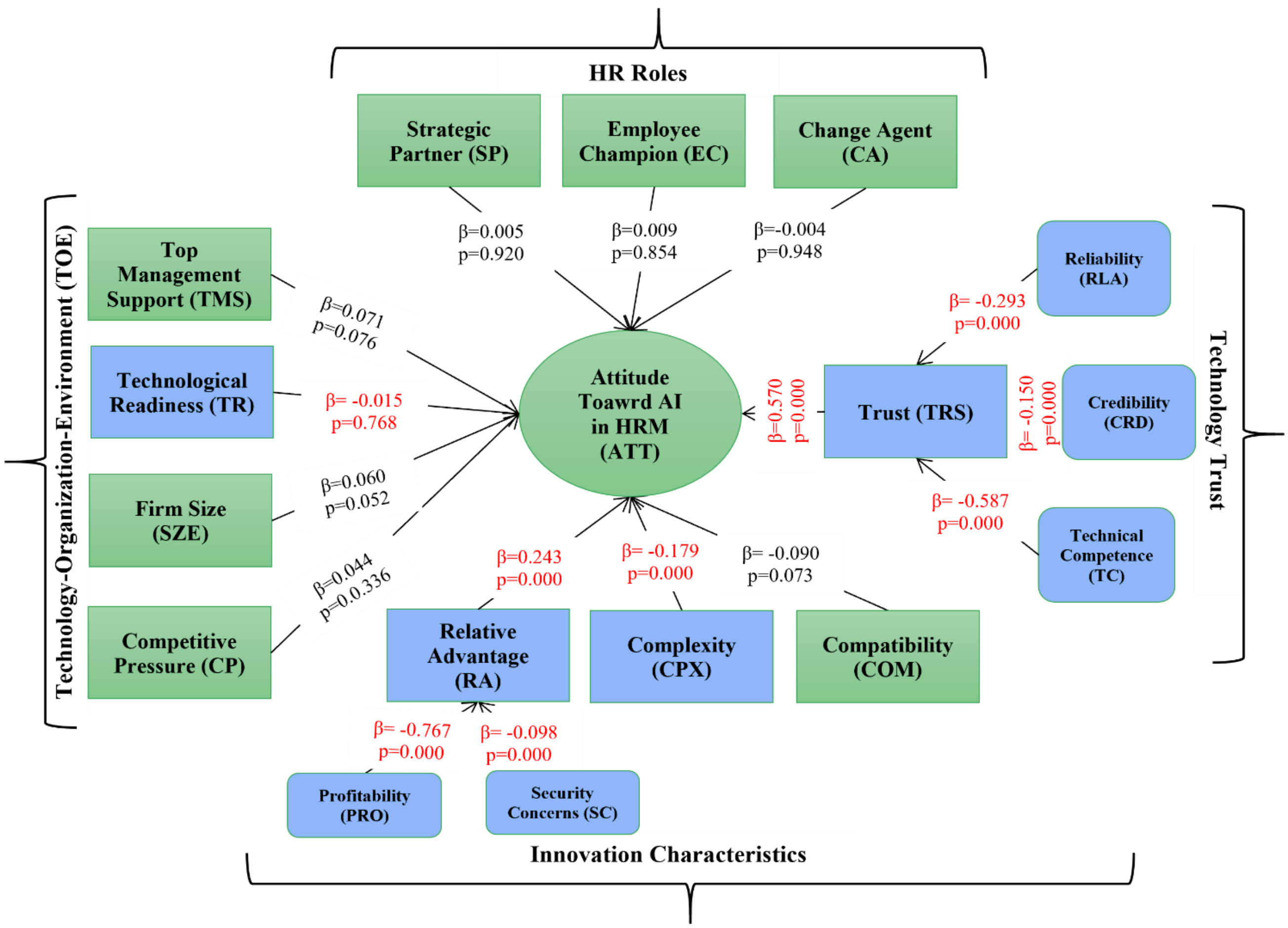

Figure 14: Research Framework Findings Review
Source: Author's Construction

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 HR, 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) attitude and level 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, organization 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 (L. Tornatzky et al., 1990), HR roles theory (Ulrich, 1997b), 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' levels 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 them. 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 their 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 analysis has 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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5. Hmoud, B. (2021). Assessing hr leaders' attitude toward the adoption of artificial intelligence in recruitment. Journal of EcoAgriTourism. 17 (1), 20-32, 2021. ISSN: 1844-8577.

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APPENDIX

Appendix (1) Factors Pattern Matrix[a] and communalities

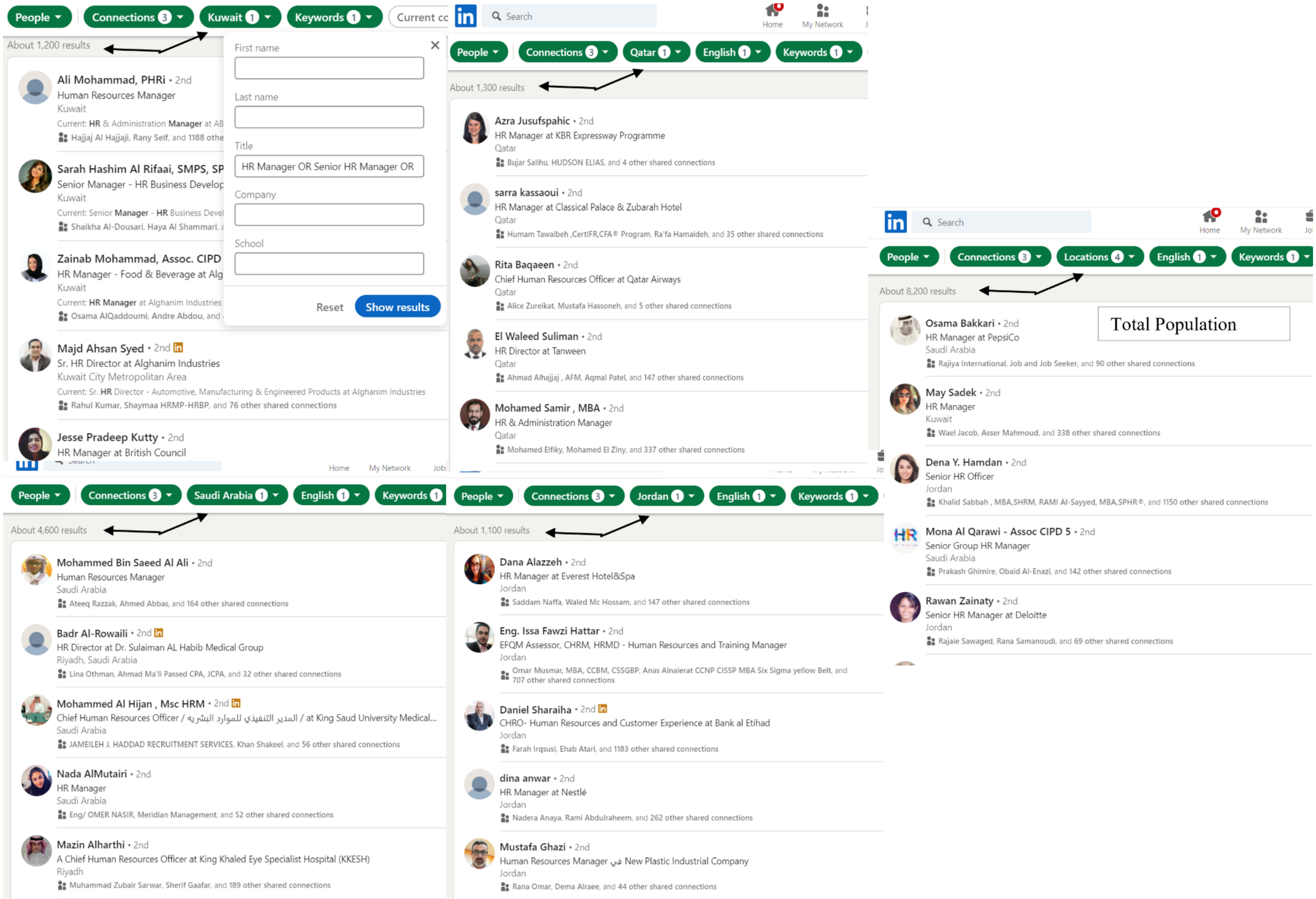
Items	Component										
	1	2	3	4	5	6	7	8	9	10	Extraction
AE1		0.44									0.67
AE2		0.30									0.49
AE3							0.43				0.64
AE4		0.36					0.40				0.72
AE5							0.66				0.68
ATT1				0.47					0.38		0.72
ATT2				0.84							0.86
ATT3				0.83							0.85
ATT4				0.91							0.85
ATT5				0.71							0.78
ATT6				0.91							0.89
CA1		0.63									0.61
CA2		0.65									0.64
CA3		0.64									0.65
CA4		0.66									0.66
CA5		0.63									0.64
COM1					0.79						0.73
COM2					0.71						0.63
COM3					0.84						0.77
COM4					0.82						0.71
CP1								0.80			0.72
CP2								0.69			0.69
CP3								0.80			0.70
CP4								0.91			0.78
CPX1			0.64								0.52
CPX2			0.64								0.67
CPX3			0.73								0.62
CPX4			0.55								0.70
CRD1	0.64										0.71
CRD2	0.57								0.62		0.86
CRD3	0.74										0.84
CRD4	0.72										0.66
EC1							0.76				0.64
EC2							0.66				0.56
EC3							0.67				0.69
EC4							0.70				0.75
EC5		0.32					0.34				0.69
PRO1	0.82										0.71

PRO2	0.86										0.77
PRO3	0.95										0.82
RA1	0.84										0.78
RA2	0.77										0.73
RA3	0.78										0.74
RA4	0.83										0.75
RA5	0.78										0.84
RLA1	0.81										0.76
RLA2	0.64										0.69
RLA3	0.73										0.82
RLA4	0.70										0.67
SEC1			0.81								0.75
SEC2			0.78								0.76
SEC3			0.80								0.79
SP1		0.69									0.63
SP2		0.86									0.73
SP3		0.79									0.64
SP4		0.89									0.79
SP5		0.85									0.71
SZE1										0.76	0.80
SZE2										0.75	0.81
TC1	0.68										0.70
TC2	0.76										0.79
TC3	0.57								0.63		0.85
TC4	0.58								0.57		0.85
TMS1						0.90					0.83
TMS2						0.84					0.76
TMS3						0.87					0.86
TMS4						0.85					0.80
TR1					0.48	0.35					0.65
TR2					0.34						0.50
TR3					0.38						0.71
TR4					0.52						0.62
TRS1	0.47								0.56		0.79
TRS2	0.59								0.34		0.77
TRS3	0.57										0.73

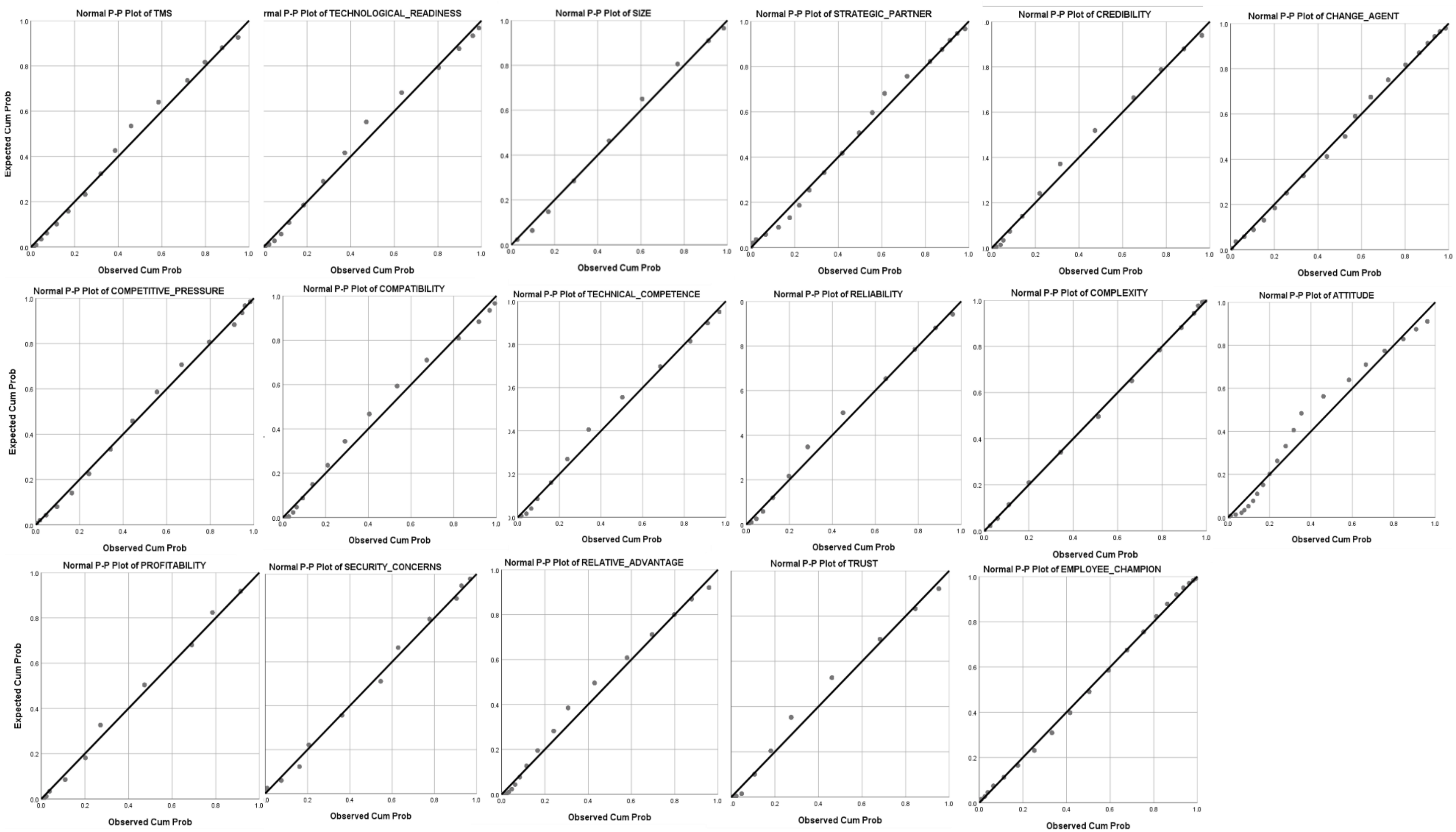
Extraction Method: Principal Component Analysis. Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 11 iterations.

Source: Author's Calculation

Appendix (2) Defining Research Population



Appendix (3) P-P plots for the Research Variables



Source: Author's Construction

Appendix (4) Research Constructs Collinearity Statistics and Correlation Coefficient

Variables	Tolerance	VIF	RA	COM	CPX	TR	CP	TRS	SP	CA	EC	TMS	SZE	ATT
RA	0.48	2.10	1.000											
COM	0.64	1.57	.279**	1.000										
CPX	0.92	1.09	-.118**	-.103**	1.000									
TR	0.73	1.36	.175**	.320**	-.093*	1.000								
CP	0.79	1.26	.223**	.283**	-.108**	.212**	1.000							
TRS	0.47	2.13	.527**	.298**	-0.056	.142**	.198**	1.000						
SP	0.50	2.01	.133**	.175**	-0.043	.104**	.118**	0.027	1.000					
CA	0.40	2.50	.126**	.106**	-0.021	0.050	.092*	.090*	.534**	1.000				
EC	0.57	1.75	-0.009	-0.007	0.019	-0.061	0.001	-.085*	.346**	.458**	1.000			
TMS	0.74	1.34	.181**	.238**	-0.057	.309**	.182**	.162**	.156**	.129**	-0.029	1.000		
SZE	0.94	1.06	-0.047	-0.041	-.111**	0.009	-0.027	-.085*	0.056	0.044	0.052	-0.001	1.000	
ATT	Independent Variable		.431**	.195**	-.177**	.145**	.206**	.458**	0.062	.081*	-0.044	.141**	0.014	1.000

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

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

Source: Author's Calculation

Appendix (5)
QUESTIONNAIRE

Dear Mr./ Ms. ………...

Good Day,

As part of my PhD studies, I am conducting research that aims to assess the HR Leader's attitude toward Artificial Intelligence (AI) applications in HRM. Specifically, investigate the effect in which Innovation Characteristics, Technology Trust, HR roles, and specific organizational and environmental factors have on the HR leaders’ attitude toward the adoption of AI in HRM.
Below, I share with you a link to a previously published article here on LinkedIn about the research phenomenon. The article addresses the trending contribution of AI to HRM and provides examples of contemporary AI applications which is used to process specific HRM task.

Artificial Intelligence in Human Resources Management: It is coming and it is going to affect your job, Where do you Stand?

Kindly note that you have been selected within the research sample and I highly appreciate your participation. What I can promise in return is to publish the result on my page, HR professionals Middle East Network, and direct inbox message to you as well. The research will provide valuable input to your respected company with conclusions about the trends, adoption determinants, competitive pressure, and HR leaders attitude toward using AI solutions in HRM.

No personal information about your identity or your employer will be collected, the responses are completely anonymous, and confidentiality is guaranteed.

Appreciate your participation by dedicating a few minutes to fill the survey by clicking on the flowing link

Artificial Intelligence (AI) in Human Resources Management (HRM) - Google Forms

Bilal Hmoud

Email: bilal.ibrahim.t@gmail.com

University of Debrecen

General Information				
Country of Employment	Jordan	☐	Kuwait	☐
	Saudi Arabia	☐	Qatar	☐
Age Category	Less than 25 Years	☐	41-50	☐
	31-40	☐	More 50 years	☐
	25-30	☐		
Academic Level	Secondary / High school	☐	Master’s degree	☐
	Certificate/Diploma	☐	PhD	☐
	Bachelor’s degree	☐		
Seniority in HRM (Experience)	Less than 3 years	☐	11-14 years	☐
	3-6 years	☐	More than 14 years	☐
	7-10 years	☐		
Job Title	Chief Human Resources Officer	☐	Senior HR Manager	☐
	HR Director	☐	HR Manager	☐
Firm Size / Employees Headcount	< 100 employees	☐	500-999	☐
	100-199	☐	> 1000 employees	☐
	200-499			
Firm Size / Annual revenue ($ million)	< 3	☐	50-100	☐
	3-10	☐	> 100	☐
	11-49	☐		

Kindly Select the option of which best reflects your answer AI = Artificial Intelligent HRM = Human Resources Management						
1 = Strongly Disagree, 2= Disagree 3= Neutral, 4= Agree, 5= Strongly Agree						
Compatibility		**SD**	**D**	**N**	**A**	**SA**
1.	AI is compatible with existing HRM practices	1	2	3	4	5
2.	AI applications in HRM is consistent with our organization's culture and value system	1	2	3	4	5
3.	AI applications in HRM fits the work style of the company	1	2	3	4	5
4.	Using AI applications in HRM is compatible with our organization's IT policies	1	2	3	4	5
Relative Advantage		**SD**	**D**	**N**	**A**	**SA**
1.	I find AI applications to be useful for HRM in my company (e.g., increase productivity, efficiency)	1	2	3	4	5
2.	AI applications support HRM to make the right decisions and take the right actions	1	2	3	4	5
3.	AI applications improve the quality of decisions and actions for HRM and reduce bias	1	2	3	4	5
4.	AI applications offer new opportunities for HRM	1	2	3	4	5
5.	AI applications can support HRM to achieve a competitive advantage	1	2	3	4	5
Complexity		**SD**	**D**	**N**	**A**	**SA**
1.	AI-based applications are complex to implement in HRM	1	2	3	4	5
2.	AI applications are a complex process, and it is hard to learn how it works	1	2	3	4	5
3.	Integrating AI applications into our HRM work practices is very difficult	1	2	3	4	5
4.	AI applications in HRM development is a complex process	1	2	3	4	5
Profitability (Cost saving)		**SD**	**D**	**N**	**A**	**SA**
1.	AI applications in HRM benefits are greater than the costs of their adoption	1	2	3	4	5
2.	My Company can avoid unnecessary cost by using AI applications in HRM	1	2	3	4	5
3.	AI applications in HRM can increase the profitability of my company	1	2	3	4	5
Security Concerns		**SD**	**D**	**N**	**A**	**SA**

1.	I have concerns about my company data security from AI applications in HRM	1	2	3	4	5
2.	I have concerns about our customers' data security from AI applications in HRM	1	2	3	4	5
3.	I have concerns about data privacy and confidentiality from AI applications in HRM	1	2	3	4	5
Top Management Support		**SD**	**D**	**N**	**A**	**SA**
1.	The Top Management has an open attitude towards technological changes in HRM and encourages the use of intelligent systems	1	2	3	4	5
2.	Top Management will likely invest funds in AI-HRM applications	1	2	3	4	5
3.	Top management understands the opportunities provided by AI applications in HRM	1	2	3	4	5
4.	Our top management proactively makes efforts for the adoption of new emerging technologies	1	2	3	4	5
Technological Readiness		**SD**	**D**	**N**	**A**	**SA**
1.	The IT system in my company can support HRM AI applications	1	2	3	4	5
2.	My company knows how AI applications can be used to support HRM	1	2	3	4	5
3.	My company is highly computerized with internal and external network connection	1	2	3	4	5
4.	My company has sufficient IT resources and skills to support the implementation of AI applications in HRM	1	2	3	4	5
Competitive Pressure		**SD**	**D**	**N**	**A**	**SA**
1.	My company under pressure from competitors to adopt AI applications in HRM	1	2	3	4	5
2.	My company needs to utilize AI applications in HRM to maintain its competitiveness in the market	1	2	3	4	5
3.	My company actively keeps tracking of newly used IT by competitors	1	2	3	4	5
4.	Our competitors have already started using AI applications in HRM	1	2	3	4	5
Reliability		**SD**	**D**	**N**	**A**	**SA**
1.	AI-based applications work in a consistent and predictable manner	1	2	3	4	5
2.	I can forecast in advance how AI will work for a specific HRM task	1	2	3	4	5
3.	AI-based applications will consistently perform under a variety of circumstance	1	2	3	4	5
4.	As an HRM solution, AI applications are very predictable	1	2	3	4	5
Credibility		**SD**	**D**	**N**	**A**	**SA**
1.	AI applications in HRM would operate in is a truthful and non-biased manner	1	2	3	4	5

2.	I AI applications support HRM integrity and trust of employees and candidates	1	2	3	4	5
3.	AI applications would operate in HRM best interest	1	2	3	4	5
4.	AI applications are safe, adequate, and error-free	1	2	3	4	5
Technical competence		**SD**	**D**	**N**	**A**	**SA**
1.	AI applications are competent and effective in processing HRM tasks	1	2	3	4	5
2.	AI applications are capable and proficient in autonomously processing HRM tasks	1	2	3	4	5
3.	AI applications have the features required to perform HRM work activities	1	2	3	4	5
4.	AI applications provide a good alternative solution for HRM	1	2	3	4	5
Trust		**SD**	**D**	**N**	**A**	**SA**
1.	I can depend and rely on AI-HRM applications	1	2	3	4	5
2.	AI applications are straight, trustworthy, and legitimate	1	2	3	4	5
3.	I trust AI-based applications in HRM	1	2	3	4	5
Human Resources Roles **Kindly Select the option of which best reflects your answer**						
1 = Very Low, 2= Low 3= Medium, 4= High, 5= Very High						
In my Company HR helps the organization to?		**VL**	**L**	**M**	**H**	**VH**
1.	Accomplish business goals	1	2	3	4	5
2.	Improve operating efficiency	1	2	3	4	5
3.	Take care of employee's personal needs	1	2	3	4	5
4.	Adapt to change	1	2	3	4	5
In my Company HR is seen as?		**VL**	**L**	**M**	**H**	**VH**
5.	A business partner	1	2	3	4	5
6.	An administrative expert	1	2	3	4	5
7.	A champion for employees	1	2	3	4	5
8.	A change agent	1	2	3	4	5
In my Company HR works to?		**VL**	**L**	**M**	**H**	**VH**
9.	Align HR strategies and business strategy	1	2	3	4	5
10.	Monitor administrative processes	1	2	3	4	5

11.	Offer assistant to help employees meet family and personal needs	1	2	3	4	5
12.	Reshape behavior for organizational change	1	2	3	4	5
In my Company HR develops processes and programs to?		**VL**	**L**	**M**	**H**	**VH**
13.	Develop HR strategies to accomplish the business strategy	1	2	3	4	5
14.	Efficiently process documents and transactions	1	2	3	4	5
15.	Connect with employees and hear their voice	1	2	3	4	5
16.	Help the organization transform itself	1	2	3	4	5
In my Company HR effectiveness is measured by its ability to?		**VL**	**L**	**M**	**H**	**VH**
17.	Help make strategy happen	1	2	3	4	5
18.	Efficiently deliver HR processes	1	2	3	4	5
19.	The level of employees' engagement and satisfaction	1	2	3	4	5
20.	Help the organization anticipate and adapt to future issues	1	2	3	4	5
Attitude Toward Adopting AI in HRM						
1 = Strongly Disagree, 2= Disagree 3= Neutral, 4= Agree, 5= Strongly Agree		**SD**	**D**	**N**	**A**	**SA**
1.	In general, AI applications in HRM is an improvement for the company	1	2	3	4	5
2.	Utilizing AI applications in HRM is a good idea	1	2	3	4	5
3.	In my opinion, it is desirable to apply AI applications in HRM	1	2	3	4	5
4.	If AI-HR applications are available now, I think I would try it	1	2	3	4	5
5.	I intend to explore the possible benefit of AI applications in HRM	1	2	3	4	5
6.	I think I would source AI applications in soon future	1	2	3	4	5