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Adoption Factors of Artificial Intelligence in Human Resources Management

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ABSTRACT

The phenomenon of artificial intelligence has been widely studied in several areas. In opposite, in terms of AI in HRM, the literature shows limited research on the adoption factors of artificial intelligence (AI) in HRM. AI has been enrolled in several HRM's areas starting from staffing till management performance or compensation. A set of suggestions on how to adopt AI in HRM has been raised. This piece of research aims to identify the adoption factors of six scenarios of AI in HRM. These scenarios are turnover prediction with artificial neural networks, candidate search with knowledge-based search engines, staff rostering with genetic algorithms, HR sentiment analysis with text mining, résumé data acquisition with information extraction and employee self-service with interactive voice response. As a result, compatibility, relative advantage, complexity, managerial support, government involvement, and vendor partnership are determinants affected factors of AI adoption in HRM. This paper tries to address new insights for practitioners and academics by minimizing the risks associated with AI adoption in some areas of HRM through exploring determinant factors of adoption.

Keywords: Artificial intelligence, Human resource management, AI Adoption factors

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1. Introduction

Smart software, cloud technology and digitalization have already changed methods of running departments in almost every organization, including particularly HRM area. Recently, Artificial intelligence (AI) is considered the most advance development in HRM technologies (IBM, 2020).

These technologies are facilitating the implementing of big data analysis, machine learning and deep learning in the HR area increasing HRM efficiency (EY, 2020).
AI is defined as a machine or computer system applied to automatically perform a task that requires a level of intelligence to be accomplished (Nilsson, 2014). It refers to a trained machine intelligent to perform like a human. Wang & Lin (2018), simplified the concept of AI as a machine/software which is able to mimic human intelligence.

Literature explains AI in HRM as a human-computer interaction function that enhances management efficiency to improve the functional procedure for collecting, maintaining and validating data of employees (Bhardwaj, Singh, & Kumar, 2020). It is also defined as a form of HRM software that is able to generate strategies based on data to simplify the management of the human resource department (Bataineh, 2017). To summarize, these data have enrolled in recruiting, selecting, performance management, compensation and talent acquisition as a result of AI adoption in HRM (EY, 2020).

There is no doubt on the key role of AI in HRM (Wang & Siau, 2019). Some evidence could be found in Lengnick-Hall, Neely, & Stone (2018). They claimed that organizations can take advantages of AI in recruiting by designing job description, and afterwards collecting and analysing candidate data from several sources. Furthermore, potential candidates could be characterised and contacted for an interview through several e-communication channels (Zhu, Corbett, & Chiu, 2020). Besides the previous advantages, AI applications offers also the possibility to conduct Video interviews over the internet with potential candidates, and analyse attitudes, interactions and body language screening candidates who potentially better fit with organization's demand (Vinichenko, et al., 2019). All of these could be done without human intervention.

Another example of advantages using AI in HRM could be found in analysing employee behaviours, attitudes and emotions that could affect job performance (Todolí-Signes, 2019). The results of this kind of analysis could improve employee satisfaction and productivity (Todolí-Signes, 2019).

This list if advantages of implementing AI in HRM could be much longer. In fact, many applications of AI in HRM are still at a conceptual stage and they have not been implemented or tested yet on commercial sectors, probably, due to the fact that the driving factors for AI adoption in HRM are still unclear (Lengnick-Hall, Neely, & Stone, 2018).

Overall, this piece of research aims at identifying and analysing adoption factors fostering AI in HRM. To do so, existing literature in Google scholar, Emerald Insight and Elsevier-ScienceDirect has been analysed. Particularly, studies which are focusing on the role of AI in HRM have been selected to be analysed.

It is important to highlight that studies validating AI technology in HRM, or analyzing success factors impacting on AI adoption in HRM, are limited. Hence, this study offers a framework to explore success factors impacting on AI adoption in HRM. To do so, a mainstream process between success factors impacting on AI adoption (Chen, 2019) and scenarios of AI in HRM (Strohmeier & Piazza, 2015) are discussed, as it could be seen in Figure 1.

Particularly, the success factors that have been considered are compatibility, relative-advantage, complexity, managerial support, government involvement, and vendor partnership. While on the scenarios of AI in HRM side, they are turnover prediction with artificial neural networks, candidate search with knowledge-based search engines, staff rostering with genetic algorithms, HR sentiment analysis with text mining, résumé data acquisition with information extraction and employee self-service with interactive voice response.

Other factors or scenarios could be added, but this piece of research is built on the previous work done by Chen (2019) and Strohmeier and Piazza (2015).

Along the process of the model developed the following research question will be answered:

What are determinants adopting factors of AI in HRM?

The model (Figure 1) will be tested by validating data available in databases specialized in AI and HRM.

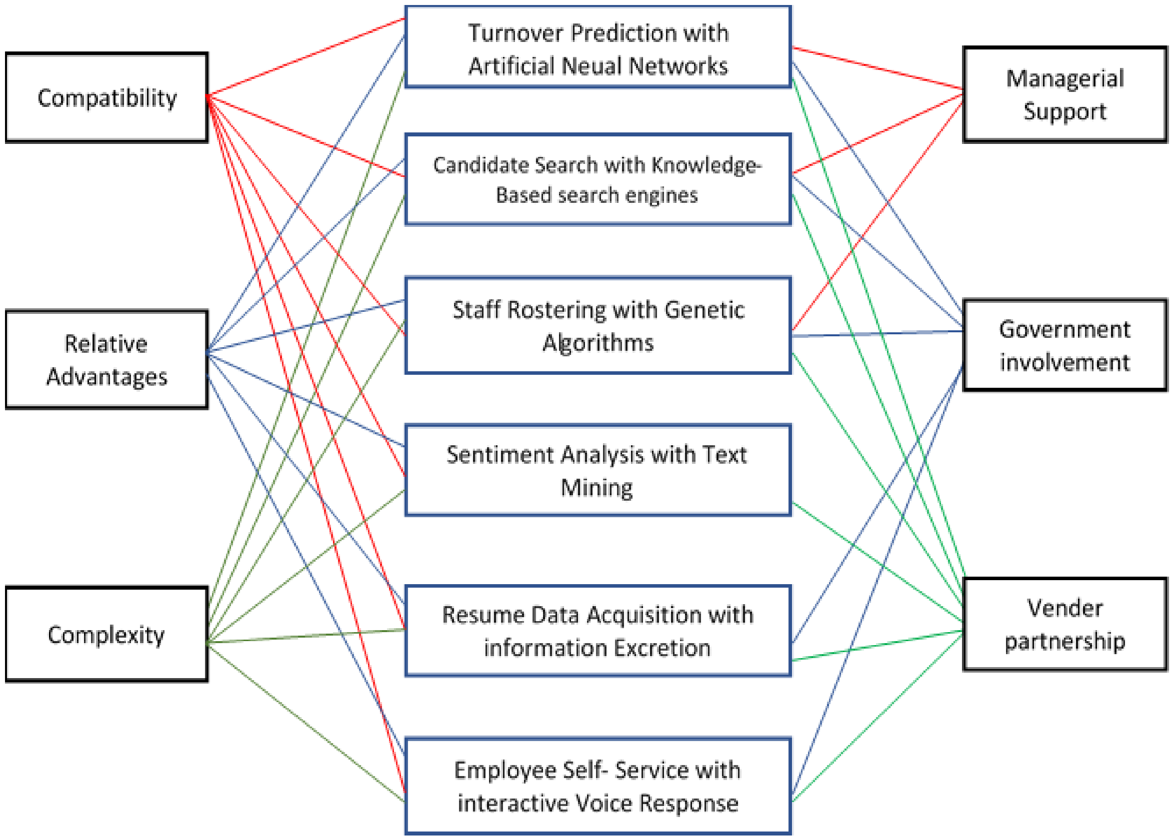

Figure 1: Success factors for adopting AI in HRM scenarios

2. Methodology

The present study is built based on a narrative literature review with the intent to joint two different research streams in order to aggregate knowledge and to identify common patterns on the adoption factors of AI in HRM (Rzepka & Berger, 2018). The first part of this paper serves as a theoretical foundation by pointing out the conceptual frame of AI and their building units. The second part describes AI scenarios in HRM. The third part build the relationships between adoption factors and scenarios. That is, it examines AI adopting factors in HRM scenarios. All of these steps are supported by a narrative literature review in Google scholar, Emerald Insight and Elsevier-ScienceDirect.

3. Result Analysis and Finding

3.1. The Conceptual Frame of AI and Its Building Units

Artificial intelligence (AI), is one of the most ambitious dreams so far, where humans are willing to design a machine able to mimic humans in terms of thinking, reasoning or learning. Therefore, AI aims to reproduce human mental activities with the support of machines, in areas such as understanding, perception or decision (Lexcellent, 2019).

The definition of AI has been changed over time due to rapid changes in innovation and technology (Kok, Boers, Kosters, Putten, & Poel, 2009). For instance, Illustrated Oxford Dictionary (2003) defined AI as “the theory and development of computer systems that are able to perform tasks that usually require human intelligence as it could be decision-making or speech recognition”. However, Wamba, Bawack, Guthrie, Queiroz, & Carillo (2020) defined AI as “machines or computer systems capable of learning to perform tasks that normally require human intelligence”. Broader definitions of AI refer to the tools and insights that AI uses and adopted in many fields, such as computer science, operations research, psychology, philosophy, neuroscience, cognitive science, linguistics, control theory, probability, optimization and logic (ScienceDaily, 2020).

To understand AI scientifically, we should analyse the building blocks that constitute AI. According to Boisseau & Wilson (2019), Deep learning and Machine learning are the basic building units of AI.

The term Machine Learning (ML), refers to a computer program that can learn to produce a behaviour that is not explicitly programmed by the programmer (Joshi, 2020). Machine learning algorithms use data to generate and refine rules, then the computer decides how to respond based on what it has learned from the data. The key here is that you’re letting the data guide the development of rules (Boisseau & Wilson, 2019).

On other hand, deep learning is a subset of machine learning, which has been introduced to support machine learning to achieve the desired goal of AI (Guo, et al., 2015).
According to PWC Global artificial intelligence study released in 2017 (PwC, 2017), AI will impact the GDP of countries by 2030 as the following. China 26.1%, North America 14.5%, 11.5% Southern Europe,10.4% Developed Asia, 9.9% Northern Europe, 5.6% Africa, Oceania, & other Asian markets, 5.4% Latin America, which mean 15.7$ trillion potential GDP gain by 2030. Therefore, the AI’s momentum will expand to cover almost all sectors and departments in the organizations (Harvard, 2017). One of these departments will be HRM (Stanley & Aggarwal, 2019).

AI, Machine learning and deep learning literature have offered a broad range of applications in HRM area so far (Rocabert, 2017). These applications are covering different tasks, including recruiting, selection, performance assessment and performance management (EY, 2020). For instance, Natural Language Processing that develops human-like response and personalized expressions called chatbots (Kocaleva, Stojanov, Stojanovik, & Zdravev, 2016). A chatbot is one of the applications of deep learning which is being expanded in recruiting and selection (Nawaz & Gomes, 2019).

Consequently, the next part will explain deeply the practical scenarios of AI in HRM.

3.2. AI Scenarios in HRM

Human resources are widely considered as one of the most valuable assets of any organization (Markoulli, Lee, ElizaByington, & Felps, 2017), and successfully managing this asset is considered a crucial managerial duty for achieving sustainable success (Armstrong, 2016). In HRM, updated technology is essential to manage and solve tasks successfully, as well as to enhance or at least maintain employees’ performance (Bataineh, 2017). One of the most recent technologies having higher potential in HRM is AI (Bhardwaj, Singh, & Kumar, 2020).

They're not that many studies on AI adoption in HRM in Academia so far. We build our work on the previous work done by Strohmeier and Piazza (2015). They explored six application scenarios of AI in HRM: turnover prediction with artificial neural networks, candidate search with knowledge-based search engines, staff rostering with genetic algorithms, sentiment analysis with text mining, resume data acquisition with information excretion and employee self-service with interactive voice response. All of them are related to HRM practices. They are further analysed in the following subsections.

3.2.1. Turnover Prediction with Artificial Neural Networks

Artificial Neural Networks (ANNs) are information processing systems that link different information processing units with different mathematical models (Walczak, 2016). ANNs provide a huge amount of knowledge to improve managerial decision making (Tkáˇc & Verner, 2016) , as well as, to facilitate managerial tasks and responsibilities.

An application scenario of ANNs in HRM is the prediction of employee turnover (Strohmeier & Piazza, 2015). Employee turnover is the voluntary resignation of employees for personal reasons. These reasons are potentially linked with historic employee data such as age, seniority, salary, qualifications, position, gender and family concerns. Employing ANN based on employee data could discover highly complex influencing patterns of employee turnover.

This prediction, especially in the case of good performing employees is critical for the organization since it could help to avoid turnover, or at least to be ready to replace employees faster. Therefore they would be able to maintain productivity in a highly competitive market.

3.2.2. Candidate Search with Knowledge-Based Search Engines

Knowledge-based search engines are described as tools able to detect and recognize queries in internet-based content and to use this recognition to organize search results (Otegi, Arregi, & Ansa, 2015) that guide users to improve their queries interactively. Therefore, they work both reducing time-consuming and also increasing knowledge representation related to inquiries.

An application scenario of knowledge-based search-engines in HRM is looking for candidates (Strohmeier & Piazza, 2015).

Looking for the most suitable candidate is not an easy job. Organizations use to invest a tremendous amount of time and effort in order to equip vacant positions. The pool of qualified passive candidates is exponentially larger than the number of applicants actively seeking an open role. Having the ability to efficiently search the entire universe of possible candidates allows for a more inclusive and effective search. Therefore, using AI to screen resumes and integrated candidate information into the recruitment process could facilitate interview scheduling or automate the application process.

This technology would be able to automate parts of the recruiting and selection process by offering reasonable details on the potential candidates (Luger, 2005).

3.2.3. Staff Rostering with Genetic Algorithms

Genetic algorithms are problem-solving techniques inspired by biological technology to identify the goodness of the individuals (Shukla, Pandey, & Mehrotra, 2015). Genetic algorithms generate solutions according to a specified objective function and problem specific constraints (Esch, Black, Franklin, & Harder, 2020).

An application scenario of genetic algorithms in HRM is staff rostering (Strohmeier & Piazza, 2015). Staff rostering addresses optimal tasks for each employee, through integrating the mental and physical capability of employees with task requirements (Ijjina & Chalavadi, 2016). The resulting optimization problem refers to optimization problem takes into account multiple criteria, such as costs, job-person fit, and employee preferences, and is characterized by multiple constraints pertaining to domain-specific aspects, such as maximum working time, recreation times, and qualification requirements, among others.

3.2.4. Sentiment Analysis with Text Mining

Functionalities of text mining techniques include categorization of text, summarization, topic detection, concept extraction, search and retrieval and document clustering (Hashimi, Hafez,

& Mathkour, 2015). Title detection and tracking and content summarization from predefined categories have several roles in facilitating functionality within departments in the organization (Kaushik & Naithani, 2016).

The application scenario of text mining in HRM is sentiment analysis (Strohmeier & Piazza, 2015). Being able to know the sentiments of employees, managers and HR stakeholders related to HR-relevant aspects constitutes valuable information to identify strengths and weaknesses of HRM. Such opinions and sentiments are increasingly expressed on social media, web-based documents on employer rating websites or blogs. Some examples of relevant aspects that could be included in such sentiment analysis could be employee satisfaction, compensation ratios, career possibilities, quality of training or leadership style.

Identifying opinions and sentiments on a specific issue through interactive e-platform would support decision-makers in planning for the short and long term through forecasting and predicting the next step for HRM stakeholders (Akilan, 2015).

3.2.5. Resume Data Acquisition with Information Excretion

Information extraction (IE) is about extracting potential information nuggets from data. The main aim of IE is to extract structured data from unstructured or semi-structured data (Nasar, Jaffry, & Malik, 2018).

An application scenario of IE in HRM is résumé data acquisition (Strohmeier & Piazza, 2015). Through the recruitment process, the HR department revises a plethora number of résumés in text documents format. These text documents then have to be processed by humans, then relevant information has to be manually extracted and entered into human resource information systems to continue the recruiting process

Through IE, this analysis could be done automatically by extracting relevant information from the resume, as it could be the name, address, job titles, work periods, names of previous organizations, qualifications, etc., without human intervention in order to provide this information into HR information systems (Moreno & Redondo, 2016). As a reflection, the increased speed of further processing of applicant data offers the potential to decrease respective costs.

3.2.6. Employee Self-Service with Interactive Voice Response

Interactive voice response (IVR) works on increasing interaction between human and computers via voice (Howell, Harrison, Burris, & Detert, 2015). Such voice-based interactions between humans and computers have already been implemented within several departments such as customer service, marketing and HRM (Hildebrand, et al., 2020).

An application scenario of interactive voice response in HRM is employee self-service (ESS) (Strohmeier & Piazza, 2015). ESS aims to shift the technology-based of HR tasks from HR professionals to employees. In general, ESS works on transfer some operational tasks from HRM's employees to HRM stockholders such as updating personal data, changing benefits, registering for a training program or tracking employee performance which enhance efficiency gains (Vardarlier & Zafer, 2019). Another application of IVR is voicebots that is able to communicate with the employees to solve and understand their problems, so they could guide them in order to get the optimal results (Evseeva, Kalchenko, Evseeva, & Plis, 2019).

Overall, specific scenarios have proofed the be relevant in AI application in HRM. They open the door for organizations to take advantages of AI in improving outcomes of specific HRM tasks (Finlay, 2017). At this point, the question now is which are the success adopting factors in order to leverage the advantages of AI in HRM (Lengnick-Hall, Neely, & Stone, 2018). The next section seeks to deepen the answer to this question.

3.3. Adopting Factors of AI in HRM Scenarios

AI can create enormous benefits for organizations, but it can also bring risks and convert active into a passive situation if the organizations are unable to design a full framework in order to adopt factors of AI successfully (Wanner, Heinrich, Janiesch, & Zschech, 2020). Success factors are the necessary enablers leading to the successful implementation of AI. These factors play a key role in improving the probability of success for decision-makers. As in any other technology implementation, multiple success factors can be found, however, this work has been built on the previous work done by Chen (2019). Within this piece of research, six success factors have been considered: compatibility, relative advantage, complexity, managerial support, government involvement, and vendor partnership. Other factors may also affect on the success of AI implementation in HRM context, but we have decided to state analysing the six listed.

Regarding compatibility, it refers to the extent to which innovation and technology are able to provide value and experience while they meet potential adopters needs (L.L.Chong & Olesen, 2017). Previous literature considers that compatibility has a positive influence both, on IT adoption in general, and on AI in particular (Verma & Chaurasia, 2019; Gangwar, Date, & Ramaswamy, 2015).

As far as relative advantage concerns, it refers to the degree to which a technology is perceived as being adding vales (Pillai & Sivathanu, 2020). Literature reveals that relative advantage has a significant effect on the adoption of AI (Mahesh, Vijayapala, & Dasanayaka, 2018; binsawad, sohaib, & hawryszkiewycz, 2019).

In terms of complexity, it concerns the extent to which technology is perceived as relatively difficult to be understood and used (Manson, 2001). The role of complexity is developed in the literature as the opposite of compatibility and relative advantage. Literature claims that by minimizing the complexity of AI technology, the adoption rate could be increased (Lu, Luo, Wang, Le, & Shi, 2015). In other words, the easier organizations would make AI integration into business operations, the greater the chance of its adoption.

Another core factor affecting AI adoption is managerial support. Literature deals with managerial support as significantly influence attitudes towards AI adoption (Awiagah & Lim, 2015). Furthermore, managerial support is necessary in order to encourage acceptance of technologies that present drastic changes for end-users (Obal & Morgan, 2018).

Government involvement and policy is the fifth factor that has a vital role in AI adoption. Alsheibani, Cheung, & Messom (2018) claim that government policy and legislation can encourage AI diffusion. Furthermore, legislation can minimize or even remove barriers to introduce new IT systems. Moreover, Halaweh (2018) point out that the adoption of new technology is a complex process, and policies set by the government could be a driver to reduce complexity.

As far as vendor partnership concerns, it can be explained as a task or activity that has been assigned out to a service provider based on a legal contract when the organization does not have an in-house technical skill (Alghamdi, 2020). Thus, the main purpose of technology and innovation vendor partnership is lowering the costs of managing and maintaining technical assets, while increasing the quality of the developments. This also allows leveraging the core capability of non-tech organizations in adopting new technologies (Jain & Khurana, 2016).

Companies achieve competitive advantages through inter and intra-organizational collaboration (Ali & Khan, 2016). Therefore, vendor partnership is one of the best practices to enhance the success rate of new technology adoption. Particularly, the adoption of AI in organizations is usually associated with IT vendors and collaborative partners because many firms are unfamiliar with AI technologies so far (Hong, Ling, & Yong, 2020). Vendor partnership has been empirically supported as one of the critical determines for innovation adoption, as well as, a core player in the AI adapting field (Chen, 2019).

4. Conclusion and Future Research

The adaptation of any AI technique to particular HRM tasks is considered a challenge for decision-makers in the HR department as it requires deep knowledge in both HR and AI (Strohmeier & Piazza, 2015). Therefore the main aim of his paper is to find a practical model for an organization that would like to adopt AI technologies and applications in specific HRM scenarios effectively.

The result of the analysis shows that the AI adoption factors analysed, affected directly on the HRM scenarios

The adoption factors considered are compatibility, relative advantage, complexity, managerial support, government involvement, and vendor partnership. Whereas the HRM scenarios analysed are turnover prediction with artificial neural networks, candidate search with knowledge-based search engines, staff rostering with genetic algorithms, sentiment analysis with text mining, resume data acquisition with information excretion and employee self-service with interactive voice response.

Therefore, this study analyses and explains the adoption factors of AI in Specific scenarios of HRM based on previous literature. We leave as a future research a further study to analyse in detail how AI is being implemented in big companies based on the model presented in this paper. Another interesting issue to consider is whether there are differences between implementation by business sectors or geographical areas.

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