UNIVERSITAT POLITÈCNICA DE VALÈNCIA

Adoption Factors of Artificial intelligence in Human Resource Management

Cumulative PhD. Thesis

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Abstract

The world is witnessing new technological advancements, which significantly impacts organizations across different departments. Artificial intelligence (AI) is one of these advancements that is widely heralded as a revolutionary technology in Human Resource Management (HRM). Professionals and scholars have discussed the bright role of AI in HRM. However, deep analysis of this technology in the HR process is still scarce.

Therefore, the main goal of this thesis is to investigate the status of AI in HRM and derive concrete implementation key factors. Through, first, building an academic framework for AI in HRM; second, analyzing the most commonly used AI applications in HR process; third, identifying the optimal ways to transfer the knowledge of AI implementation processes.

The methodology used for the investigation combines a systematic literature review and a qualitative research technique. As a basis and preparatory measure to address the research questions, an extensive literature analysis in the AI-HRM field was carried out, with a particular focus on publications of AI in HRM, HR-Big data analysis, AI applications/solutions in HRM and AI implementation. Along similar lines, the author published papers in several conference proceedings to improve the maturity of research questions.

Based on this work, the published studies illustrate the gap between the promise and reality of AI in HRM, taking into account the requirements of AI implementation as well as the applications and limitations. Subsequently, HR experts and AI consultants, who had already gained first-hand experience with HR processes in an AI environment, were interviewed to find out the truth of the dominant AI's application in HR process.

The main findings of this thesis are the derivation of a complete definition of AI in HRM as well as the status of the adoption strategies of AI applications in HRM. As a further result, it explores the usefulness and limitations of chatbots in the recruitment processes in India. In addition, derived the key factors to transfer the knowledge of AI implementation process to HR managers and employees. Challenges associated with AI implementation in the HR process and the impact of COVID-19 on AI implementation were also concluded.

Resumen

El mundo es testigo de nuevos avances tecnológicos que afectan significativamente a las organizaciones en diferentes departamentos. La inteligencia artificial (IA) es uno de estos avances, visto como una tecnología revolucionaria en la gestión de recursos humanos (RRHH). Profesionales y académicos han discutido el brillante papel de la IA en RRHH. Sin embargo, el análisis profundo de esta tecnología en el proceso de RRHH es aún escaso. Con todo ello, el objetivo principal de esta tesis es investigar el estado de la IA en RRHH y así identificar factores clave de implementación concretos. Primero, construyendo un marco académico para la IA en RRHH; segundo, analizar las aplicaciones de IA más utilizada en los procesos de RRHH; tercero, identificar las formas óptimas de transferir el conocimiento en los procesos de implementación de IA.

La metodología utilizada para la investigación combina la revisión sistemática de la literatura y técnicas de investigación cualitativa. Como base y medida preparatoria para abordar las preguntas de investigación, se llevó a cabo un extenso análisis de la literatura en el campo AI-RRHH, con un enfoque particular en las publicaciones de algoritmos de IA en HRM, análisis de HR-Big data, aplicaciones/soluciones de IA en HRM e implementación de IA. En la misma línea, el autor publicó artículos en varias conferencias que contribuyeron a mejorar la madurez de las preguntas de investigación. Con base en este conocimiento, los estudios publicados ilustraron la brecha entre la promesa y la realidad de la IA en RRHH, teniendo en cuenta los requisitos técnicos de la implementación de la IA, así como las aplicaciones y limitaciones. Posteriormente, se entrevistó a expertos en recursos humanos y consultores de IA que ya habían adquirido experiencia de primera mano con los procesos de recursos humanos en un entorno de IA para descubrir la verdad de la aplicación de la IA dominante en el proceso de RRHH.

Los principales hallazgos de esta tesis incluyen la derivación de una definición completa de IA en RRHH, así como el estado de las estrategias de adopción de aplicaciones de IA en RRHH. Como resultado adicional, se explora la utilidad y las limitaciones de los chatbots en el proceso de contratación en la India. Además, factores clave para transferir el conocimiento del proceso de implementación de IA a los gerentes y empleados de recursos humanos. Finalmente, se concluye identificando desafíos asociados con la implementación de IA en el proceso de recursos humanos y el impacto de COVID-19 en la implementación de IA.

Resum

El món és testimoni de nous avanços tecnològics, que afecten significativament les organitzacions en diferents departaments. La intel·ligència artificial (IA) és un d'aquests avanços que s'anuncia àmpliament com una tecnologia revolucionària en la gestió de recursos humans (HRM). Professionals i acadèmics han discutit el brillant paper de la IA en HRM. No obstant això, encara és escàs l'anàlisi profund d'aquesta tecnologia en el procés de HRM. Per tant, l'objectiu principal d'aquesta tesi és investigar l'estat de la IA en HRM i derivar factors clau d'implementació concrets. Primer, construint un marc acadèmic per a la IA en HRM; segon, analitzar l'aplicació de IA més utilitzada en el procés de recursos humans; tercer, identificar les formes òptimes de transferir el coneixement dels processos d'implementació de IA.

La metodologia utilitzada per a la investigació es combina entre una revisió sistemàtica de la literatura i una tècnica d'investigació qualitativa. Com a base i mesura preparatòria per a abordar les preguntes d'investigació, es va dur a terme una extensa anàlisi de la literatura en el camp IA-HRM, amb un enfocament particular en les publicacions d'algorismes de IA en HRM, anàlisis de HR-Big data, aplicacions/soluciones de IA en HRM i implementació de IA. En la mateixa línia, l'autor va publicar articles en diverses conferències que van procedir a millorar la maduresa de les preguntes d'investigació. Amb base en aquest coneixement, els estudis publicats van illustrar la bretxa entre la promesa i la realitat de la IA en HRM, tenint en compte els requisits tècnics de la implementació de la IA, així com les aplicacions i limitacions. Posteriorment, es va entrevistar experts en recursos humans i consultors de IA que ja havien adquirit experiència de primera mà amb els processos de recursos humans en un entorn de IA per a descobrir la veritat de l'aplicació de la IA dominant en el procés de recursos humans.

Les principals troballes d'aquesta tesi són la derivació d'una definició completa de IA en HRM, així com l'estat de les estratègies d'adopció d'aplicacions de IA en HRM. Com a resultat addicional, explore la utilitat i les limitacions dels chatbots en el procés de contractació a l'Índia. A més, factors clau per a transferir el coneixement del procés d'implementació de IA als gerents i empleats de recursos humans. També es van concloure els desafiaments associats amb la implementació de IA en el procés de recursos humans i l'impacte de COVID-19 en la implementació de IA.

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1. Introduction

Human Resource Management (HRM) modernization has experienced a significant evolution as technology penetrates its functions (Votto et al., 2021). From earlier inventions like the internet, HRM has found ways to employ the technology in order to improve performance, enhance employee satisfaction and reduce costs. These technologies include examples, such as ‘internet-based HRM’ (Marler & Parry, 2016), ‘electronic HRM (e-HRM)’ (Strohmeier S. , 2007), ‘Cloud computing-HRM’ (Wang et al., 2016) or ‘HRM-analysis’ (Parry & Strohmeier, 2014). Fueling this growth is the spread of enterprise resource planning (ERP) software that allows employees, on the one hand, to update their personal information, request salary certificates and request vacations without time concerns. On the other hand, it also enables managers to have access to information and data, conduct analyses, and make decisions without HR’s intervention (Panayotopoulou et al., 2007). Recently, Artificial intelligence (AI) has been promoted as the most advanced technological evolution in HRM (Bondarouk & Brewster, 2016). It describes as an intelligent machine that mimics human capabilities and intellectual behaviour in decoding external data and learning from it to attain a proper pattern (Qamar et al., 2021).

AI is a potentially transformative force that is expected to reshape the functionality of an organization’s departments (Kshetri, 2021), by the ability to analyze structured and unstructured data in complex environments (Paschen et al., 2020). These abilities are enhanced by using a broad set of applications such as natural language processing (NLP), machine learning, deep learning, artificial neural network (ANN), face recognition, data science (DS) and genetic algorithms (van der Maas et al., 2021). The three components of AI, named: big data mining, sophisticated algorithms and supercomputing, help AI to be distinguished from existence / previous technology (Prikshat et al., 2021). Such these features, AI is increasingly integrated into the management process to improve decision-making and problem-solving of routine and non-routine tasks (Cheng & Hackett, 2021). It provides better accuracy and stability to everyday tasks using an algorithm that connects quality data with fast computation services (EY, 2021).

AI applications have brought some new functionalities to HRM through navigating employees and decision makers towered the best solutions (Hogg, 2019; Pillai & Sivathanu, 2020). These advancements have gained more momentum due to the spread of data collection instruments and the potential impact of disasters on organizations (Zielinski, 2020). Therefore, AI's potential effectiveness is linked with its ability to reduce challenges associated with the HRM process (Tambe et al., 2019).

HRM refers to the practice, policy and system that influence an organization's performance. It affects performance through, but not limited to, staffing, training and development and HR planning (Taamneh et al., 2018). Another significant value is paired with developing concrete standards for job design, performance management, rewards and compensation and employee relations (Ferguson & Reio Jr, 2010). Yabanci (2019) argues that, when AI system implemented in Internal and external organizational activities at divergent levels (e.g., utilizing these systems for recruitment and selection or conducting on other HR tasks), this system tries to get access to available data and that, in consequence, it would potentially facilitate the execution of some challenging and complex HRM tasks. In this context. AI-powered solutions have been adopted among some organizations to stand against negative sequences of COVID-19 on HRM (Hamouche, 2021). These applications have a significant role in reducing the spread of viruses and minimizing hazards by facilitating a virtual workplace (Carnevale & Hatak, 2020).

AI is a data-driven technology, thus employee's data, as a resource, is reshaping the ways of managing employees, predicting their performance and maintaining their productivities (Chatterjee et al., 2021). Previously, organizations were only concerned about collecting and analysing customer data. But in this new era of digital transformation, employee data presents a huge opportunity for promoting organization performance (Larson & Chang, 2016). Using employee data correctly gives organizations powerful insights to manage their teams and to observe their performance in specific tasks. In this context, collecting, managing, visualising and analysing a massive amount of data is referred as data science (DS) (Medeiros et al., 2020). In the HRM context, DS translates employees' data into knowledge and information to support data-driven decision-making (Garcia-Arroyo & Osca, 2019). An investigation done by Müller et al. (2018) on data set of more than 800 companies between 2008 and 2014 found that investment in DS is associated with business productivity improvement by (average) five percent. In addition, a study by McKinsey (Bughin et al., 2018) argues that the potential impact of DS and AI on the global economy will be expected around 13 $ trillion by the end of 2030. This study also predicts that non-adopter of DS and AI will face a 20% cut-off from money follow by 2030. Therefore, organizations should take serious steps in the workplace to promote AI culture in their core operations (Medeiros et al., 2020).

Driven by the above-mentioned advancements, numerous scholars have demonstrated that AI could add value to HRM functions (Yabanci, 2019; Wheeler & Buckley, 2021), especially in recruiting, decision making and employees' data analysis (Black & van Esch, 2021; Dwivedi et al., 2021; Jarrahi, 2018). However, other scholars argue that AI is a close box that needs a deep analysis (Rana et al., 2021). It has a double-edged sword in the workplace (Wilkens, 2020). AI in HRM is still at a nascent stage and receiving significant attention from researchers and practitioners (Garg et al., 2021). In the opposite of other sectors (such as marketing, advertising and social media), less attention has been found around AI in HRM (Tambe et al., 2019).

The present thesis originally addresses the above-mentioned needs by conducting a systemic literature review (SLR). On the one hand, it derives a specific definition for AI in HRM. And, on the other hand, it analyses the recent known AI applications in HRM with their adoption strategy. Based on SLRs' findings, this thesis analysed the dominant AI's application in the HRM process. After that, figure out AI implementation key factors for HR managers and employees during Covid-19.

This thesis contributes to the AI-HRM literature by academically scrutinizing the current status of AI in HRM, which could highlight the real advantages of AI far away from desiderate. In addition, the best way to share the AI-implementation knowledge with HR managers and employees has been researched. Therefore, a new road map for managers and AI consultants has been developed to maximize the benefit of AI in the HR process.

2. Thesis Structure and influencing factors

Today, emerging technology is reshaping the HRM landscape. In fact, with dynamic development and wide applications of AI, the integration between organizations and employees is completely changing the automation and administrative components of HRM activities (Vrontis et al., 2021).

As stated in the introduction, the purpose of this thesis is to identify the current status of AI in HRM, based on the Fact that multidisciplinary synthesis for AI in HRM is invaluable. This thesis intends to enhance the academic literature of HRM by offering answers for five questions that are inspiring this thesis. In a parallel line, thesis questions serve as the structure and influencing factors for building embedded articles. Each question is considered to what extent the articles could contribute to its solution. The answers of these questions are embedded in the determined articles

First question: How has AI been conceptualized in the HRM context?

Addressed in article number 1 entitled, “Artificial intelligence definition, applications and adoption in human resource management: a systematic literature review”.

Second question: What are the challenges associated with AI implementation?

Addressed in the following articles: Article number 1, entitled “Artificial intelligence definition, applications and adoption in human resource management: a systematic literature review”. Also, in article number 3, entitled “Key elements in transferring knowledge of the AI implementation process for HRM in COVID-19 times: AI consultants’ perspective”.

Third question: How do organizations improve their maturity on transferring AI-implementation knowledge among HR managers and employees?

Addressed in article: Article number 3, entitled “Key elements in transferring knowledge of the AI implementation process for HRM in COVID-19 times: AI consultants’ perspective”.

Fourth question: What is the current status of AI applications in the HR process?

Addressed in articles: Article number 1, entitled “Artificial intelligence definition, applications and adoption in human resource management: a systematic literature review”. Also, in article number 2, entitled “Perspectives of Indian HR professionals on AI-powered chatbots in recruitment: multiple cases”.

Fifth question: What are the technical problems facing AI implementation in HRM?

Addressed in article: Article number 3, entitled “Key elements in transferring knowledge of the AI implementation process for HRM in COVID-19 times: AI consultants’ perspective”.

3. Research Methodology

This section sets out the methodologies used to achieve thesis's objectives. It discusses the value of academic research. Furthermore, the samples and the instruments that were used in designing research inquiries, data collection, data analysis, the systematic research procedure and the final results.

3.1 General

Research is a systemic investigation undertaken in order to assist in solving problems, identifying facts or dealing with specific phenomena (Snyder, 2019). In detail, systemic research is a set of plans and procedures that span from broad assumptions to the narrow procedures of data collection, analysis, and interpretation. The successive way of strong theoretical explanations starts from locating and analysing the literature in several databases in order to build a visual picture of existing research in a specific area. It provides a foundation for the importance of the study as well as a benchmark for comparing the results with other findings (Williams, 2007). Following, narrowing the procedures by selecting a research approach to identify the characteristics of problems according to predetermined criteria. It proceeds through: (a) identify the research gap and research problem; (b) develop research questions; (c) analyze resources; (d) formulate hypothesis; (e) develop theories or models; and (f) derive a conclusion (Ghezzi, 2020).

3.2 Systemic literature review

In order to understand how AI has been conceptualized in human resource literature. SLR has been adopted to identify, select and critically evaluate publications in order to answer formulated questions (Boell & Cecez-Kecmanovic, 2015). SLR depends on a clear plan where the criteria are selected carefully before the review is conducted. It is a deep and transparent search across multiple databases to build a coherent picture. SLR is a component of six steps including: (1) defining the research questions, (2) determining the required characteristics of primary studies, (3) retrieving samples from potentially relevant literature, (4) selecting the pertinent literature, (5) synthesizing the literature, and (6) reporting the results (Durach et al.,2017). This methodology has been used in four areas from this thesis. It is used in the first article and the first, second and fourth appendices.

In the first article, 559 papers have been subject to initial screening from Science Direct and Scopus database generated from two general terms “HRM” and “AI”. Resulted papers are covering a wide scope of AI in the HR process, such as Machine Learning in HR process, Deep learning in HR process, Speech and vision recognition in HRM and other AI applications. To evaluate the relatedness and association strength of the selected articles, VOSviewer has been used to construct and visualize bibliometric networks.

The outcomes have been served to answer the research questions of the first articles, as well as, derived procedure model for the rest of the articles in this thesis.

SLR is also used in different appendices in this thesis. It's worthy of highlighting that all appendices are considered a foundation for the core of this thesis. In the first appendix, a research article has been developed depending on literature analyzed in ISI (Web of Knowledge) to determine factors influencing employee performance. In the second appendix, the conference paper has identified the common patterns for adopting AI in HRM based on a narrative literature review. Same research methodology has been used in the fourth appendix, to investigate how literature analyzes AI transforming in HRM functions.

3.3 Qualitative analysis

To analyse the implementation and applications of AI in HRM, qualitative analysis has been used in the second and third articles. Adopting qualitative research methodology in this thesis has two reasons. First, it helps to understand the practical side of AI applications in HRM from AI consultants' and HR managers' perspectives (Higgs et al.,2009). This, in turn, allows the researcher to enrich his knowledge with the market trend of this technology. Second, this topic is relatively new and resulting in limited reach to professionals in this knowledge area (Gummesson, 2006).

In detail, using qualitative analysis in the second article helps to understand the role of chatbots in recruitment as well as the obstacles of this technology. While using qualitative analysis in the third article, facilitate identifying key factors to transfer the knowledge AI implementation process to HR managers and employees.

3.3.1 Interview Strategy

Interview or semi-structured interview is the most common technique in qualitative research (Kallio et al., 2016). It enables deep discussion between interviewer and interviewee, enriches the scope of the questions by following up the interviewee's answer with other questions, and allows the interviewee to use his expression in describing the problem and solution (Carminati, 2018).

Semi-structured interviews in this thesis are structured based on the future recommendations of other scholars. For instance, the future recommendations of Chang (2020), and Malik et al. (2021), guide us to formulate the research questions and interview questions of the third article in this thesis. The questions were determined before the interviews and developed using the interview guideline. To maintain the quality, all co-authors had involved in formulating and designing interview questions (Austin & Sutton, 2015).

All interviewees have received an invitation letter, a brief explanation of questions and the research scope based on prepared interview guidelines. Interviews' questions served in two domains. On the one hand, ensure that the potential to be interviewed matches with defined expert criteria. On the other hand, it is intended to comply with ethical requirements regarding the transparency of the process, the research objective and securing interviewees' personal data (Johnson, 2015). At the end of the interviews, data collected from interviewees are verbatim transcribed and time-stamped, so that it was possible to trace who said what and when. This type of transcription is also called "literal transcription with literary script" (Kramarić, 2016). These transcriptions served as a basis for the data interpretation (Azungah, 2018).

3.3.2 Data analysis

Thematic analysis has been used to analyze the transcribed interviews. Several phases have been adopted to identify, analyze, and report patterns (themes) within data. These themes were organized and described to generate codes. Then, clustering similar codes to produce higher-order code, which help to provide a view across different thematic landscape of data (Vaismoradi et al., 2013). Quality of coding was assured by assigned independent qualified academic persons to validate existing categories. These multiple checking procedures are called an intercoder agreement and help in maintaining the objectivity, reliability and validity of the analysis (Tuckett, 2005).

The last step of data analysis was drawn on analytical conclusions of data presented, which were generated from codes and themes. These conclusions are responded to the research questions in the interviews. Special attention was paid to causal mechanisms and connections (Castleberry & Nolen, 2018). Thus, the findings were summarized, sorted and checked against redundancies and contradictions.

ATLAS.ti has been used to interpret data and derive codes. This software belongs to sophisticated CAQDAS typology (Computer-Aided Qualitative Data AnalysisS, or

Qualitative Data Analysis Software (QDAS)). It uses widely in social science research to facilitate qualitative data analysis and generate reliable and transparent results (Paulus et al., 2019). ATLAS.ti allows scholars to search, organize, categorize, and annotate textual and visual data. Also, it supports building theories and visualizing the relationships between variables that have been coded in the data.

3.4 Ethics

Social research observations, investigations and analyses are carried out by humans, which raises ethical concerns. Therefore, this thesis is subject to Oswaldo (2021), and Shaw (2008) guidelines to maintain integrity and objectivity from the initial stages of planning this thesis until the conclusion and future research.

The core principles of social research ethics include, but are not limited to:

- Introduced the research process and the research objective to the interviewees.
- Obtained the interviewees' consent to participate and the subsequent publication of the results in advance (Consent form is available in appendix 8).
- Offered for interviewees appropriate and accessible information about the purpose, methods and intended uses of the research.
- Assuring that the research findings are communicated to the interviewees.
- Demonstrate integrity by explaining that this study is part of a doctoral thesis and assuring that the data will not be used for purposes other than those described.
- Anonymization of personal data so that no conclusions about specific interviewee or businesses field can be drawn.
- Responsible handling of the personal data (among other things, recordings and transcriptions are only stored on encrypted UPV cloud with limited access).
- Theories, methods, and research designs are clearly defined for interviewees and documented in detail.
- All stages of research design, data collecting, data cleaning, coding and analysis are documented appropriately to enhance transparency and an audit trail.

4. Articles

Building accurate and strong thesis is depending on integrating findings and perspectives of different research activities (Snyder, 2019). These activities are combining between research papers and conference proceedings, which could contribute to provide in depth analysis of specific research area (Viberg et al., 2018). Therefore, this thesis is merging between the conclusions generated from four research articles (three Scopus articles and one non-Scopus article) and three conference proceedings to analysis the actual status of AI in HRM far away from desiderates.

In detail, the core of this thesis is depending on three Scopus indexed articles while the rest of publications are available in the appendix's section. The following section includes the three main articles of this thesis, whereas appendixes includes other previous work done, mainly other conference papers and non-indexed paper. The content of the main papers, as well as their structure and logical interdependence are described below.

It should be highlighted that the initial stage in this thesis started with exploring the factors affecting on employee's performance. The result of this investigation led to publish a research article entitled "The Determinants of Employee's Performance: A Literature Review" (See appendix 1). The main conclusion from this article revealed that technology is one of the most determinant factors of employee performance. This result influenced us to investigate the most emergent technology in HRM, which led to publish a conference proceeding paper entitled "Adoption Factors of Artificial intelligence in Human Resource Management" (See appendix 2). Both of them have helped us to shed light on the need for deep analysis of AI in HRM. This fact is demonstrated in the first main article.

The **First main Article** aims to analyse the status of AI in HRM, through investigating AI's applications in HRM and the availably of clear adoption strategies for these applications. Furthermore, it derived a specific definition for AI in HRM. The conclusion revealed from the first article has been a keystone to build the **Second Article.** In detail, first article concluded that recruitment and performance management have the most AI applications in HRM. Therefore, a conference proceeding paper has been published entailed "Are we ready to implement artificial intelligence in HR performance management?" (See appendix 3). This paper revealed that AI is not fully adopted in HR performance management, which guide us to focus more on the role of AI in recruitment. Therefore, **second main article** is considered the practical side of this thesis, through focusing on the applications of chatbots in recruitment as well as the limitation of this technology. A chatbot is an AI-algorithm arm using nature luggage processing (NLP) to interact with candidates and employees.

In order to understand how we could adopt AI in HRM. I analyzed the transformative role of AI in HRM, through published a conference proceeding paper entailed “The role of Artificial Intelligence in transforming HRM functions. A literature review” (See appendix 4). The data gathered from the second article as well as the latest conference paper are helping in publishing the **Third main article**. Among other things, the third article identifies the key factors to 1) transfer the knowledge AI implementation processes to HR managers; and 2) HR managers’ strategies to facilitate AI implementation among employees. Also, challenges associated with AI implementation in the HR process at time of COVID-19.

4.1 Article 1 "Artificial intelligence definition, applications and adoption in human resource management: a systematic literature review"

Title:	Artificial intelligence definition, applications and adoption in human resource management: a systematic literature review
DOI:	10.1504/IJBIR.2021.10040005
Format:	Journal Article
Journal:	International Journal of Business Innovation and Research
Language:	English
Journal Metrics	Scopus, Q3 . Cite Score: 1.7
Status:	Entering Publication Schedule
Keywords	Artificial intelligence; human resource management; HRM; deep learning; machine learning; AI in HRM.

Abstract

This paper deals with the role of artificial intelligence (AI) in human resource management (HRM). Although AI emerged in the mid of the 20th century, current literature still offers an inconsistent view of AI in HRM. This piece of research provides an overview of the academic literature published in this field. AI and HRM, two separated research streams so far, have been analysed to aggregate knowledge and to identify common patterns on the interaction between them. The aim of this piece of paper is to analyse how AI can influence HRM and derive a specific definition of AI in HRM. Moreover, the authors discuss AI applications in HRM and current academic framework for AI adoption in HRM. The findings show a comprehensive review of the relationship between AI and HRM, identifying research gaps regarding this knowledge area, and the implications of AI concerning.

Introduction

Nowadays, digital solutions are widespread in companies worldwide. Digital transformation phenomenon has come to stay. It influences our behaviour and our way of living. Digital transformation includes all the initiatives embracing digital tools to transform companies and society (Magistretti et al., 2019). This transformation is being fostered by technologies such as big data, information knowledge management systems, cloud computing, artificial intelligence (AI) or rapid prototyping systems (Magistretti et al., 2019; Strohmeier & Piazza, 2013; Ziebell et al., 2019). It has reached all company areas including customer service, finance, production or human resource management (HRM) (Kitsios & Kamariotou, 2021).

Paying attention on HRM area, technological advancements are completely reshaping and redefining the way people work and how they are managed in organisations (Derous & De Fruyt, 2016; Yamin, 2020; van Esch & Black, 2019). HRM is moving away from its foundation administrative functionality in recruitment, selection or appraising, to more advanced progress based on automation, augmented intelligence, robotics and AI (Matsa & Gullamajji, 2019; Wang et al., 2018). From the full range of digital technologies, AI is seen as one of the most evolved, with the most significant disruptive potential (Bhattacharyya & Nair, 2019; Kitsios & Kamariotou, 2021). It's radically different from prior technologies due to its potential to transform the landscape of work, employment and society (Bailey & Barley, 2020).

As far as AI potential in HR concerns, IBM survey (2016) depicted that 66% of CEOs believed that AI could add significant value in HRM. Moreover, 54% of HRM executives stated that AI could affect the key role played by HR in organisations (Bokelberg et al., 2017). For instance, AI could be applied to HRM by implementing big data analysis in customised training and development programs for employees based on their background and practical experiences (Hilbert, 2016). Machine learning (ML), chatbots, expert system or intelligent learning platforms are other AI applications that could contribute also to enhancing HRM practices efficiency (Black & van Esch, 2020; Wang & Siau, 2019). The future of HR is being seen in both digital and human as HR leaders focus on optimising the combination of human and automated work (Sparrow et al., 2016). This combination of people and digital technologies is one of the biggest challenges: HR requires leaders and teams to develop fluency in AI while HR should be redesigned to be more personal, human and intuitive (Abdeldayem & Aldulaimi, 2020; Meister, 2019).

However, despite AI technologies' proliferation, accessibility, scalability, and ease-of-use organisations are still struggling to reach their full potential (Holmstrom, 2021). This difficulty is caused, on the one hand, by insufficient understanding of the AI concept in HRM, even though the future of HRM is intrinsically linked to AI (Bailey & Barley, 2020) and, on the other hand, an increasing amount of AI applications in HRM practices with no clear adoption strategy (Abdeldayem & Aldulaimi, 2020).

Digital technologies such as AI are said to be especially challenging and dynamic, as their adoption entails multiple, continuous, and simultaneous adjustments of organisations' resources, staffing, culture and decision-making (Holmstrom, 2021). For this reason, a clear understanding of what AI is in HRM is crucial, so that it could reduce uncertainty in decision-making processes and it would greatly simplify the ulterior adoption process.

Previous works attempting to clarify AI in HRM have failed on it. In fact, no consensus has been reached about a definition of the term. This fact increases the fuzziness in HRM departments in terms of AI and it also increases the challenge to implement AI in HRM (Jarrahi, 2018). An example of fuzziness in AI definition in HRM could be found in Wang et al. (2018). They define AI in HRM as a machine able to mimic humans in terms of thinking, reasoning and learning. While Bhardwaj et al. (2020) explain AI as a human-computer interaction that helps to improve the functional procedure of the organisation.

The increasing amount of AI applications in the HRM context and taking decisions about the most suitable one according to the company's strategy are other challenges faced by HR managers (Balakrishnan et al., 2020). Despite a significant number of companies adopting AI applications in HRM (Black & van Esch, 2020), evidence for successful harmony between AI and HRM is not yet clear, not only because AI is an ever-increasing emerging technology, but also due to the fact that AI adoption is strategies are not clear yet (Xu et al., 2020). Concerns about the complexity of AI technology, as well as about data security and privacy, present the biggest obstacles to increase the adoption of AI (Oracle, 2019).

Few researchers have studied the literature about AI in HRM so far, addressing the definition of AI (Tambe et al., 2019; Wang & Siau, 2019), AI applications (Biswal et al., 2020; Rąb-Kettler & Lehnervp, 2019) and AI adoption framework (van Esch et al., 2021; Pillai & Sivathanu, 2020). This paper, therefore, to the best of our understanding, varies from those previously conducted by synthesising to a systematic review of literature looking for a specific correlation between AI and HRM. The analysis of the integration of AI in HRM is a new point of view not studied in depth before. It is a topic not researched, specifically, in the aforementioned articles.

Therefore, this paper contributes to academia in offering a study in-depth of the contexts where AI and HRM have been effectively integrated. Hence, the main aim of the present work is to analyse, based on previous literature, the AI definition in HRM along with its applications and adoption in this context. To address this issue, a systematic literature review (SLR) has been conducted to answer the following research questions:

1 How has AI been conceptualised and generalised in the HRM context to date?

2 What is known about AI applications in HRM?

3 How these applications have been adopted so far?

In order to answer these questions, the steps followed were to firstly carry out an analysis of AI conceptualisation, and then to provide the theoretical basis used in existing studies to construct and explain AI in the HRM context. Secondly, after describing the main features of this technology, common AI applications pursuing competitive advantage in HRM in organisations have been shown.

This paper contributes to the previous literature in three different ways. As the literature has shown to date an ambiguous vision regarding AI definition in HRM (Prem, 2019), the first contribution of this paper constitutes the setting of a clear definition for AI in HRM. Many of the previous studies are empirical (e.g., case studies), and there is a lack of theory building (Strohmeier S., 2007; Ziebell et al., 2019), on the other hand, this study also enriches the conceptualisation and theoretical frameworks of AI applications in HRM (Bokelberg et al., 2017). Finally, this piece of research sheds light on the relevance of laying solid foundations needed to build a clear framework for AI adoption in HRM. Identifying a framework for adopting AI applications in HRM brings integration of human resources and business strategies at the organisation's high level of decision-making. This integration is especially relevant in a context where HRM requires people and manage people, and AI offers solutions that imply transforming the relationship between people and technology at work (Oracle, 2019). Such contributions provide an outline of how AI applications in HRM could be generally successfully adopted (Jatobá, et al., 2019).

This paper does not only identify research gaps in previous literature but also proposes an emerging approach for future research, which may encourage academics and HR managers to progress in the area of AI in HRM. This piece of research may help to develop new knowledge for a better understanding of mechanisms and techniques of AI adoption in HRM.

Methodology

A SLR is defined as a review of highly structured questions depending on systematic and explicit methods to identify, select and critically appraise relevant research (Allen, 2009; Thomé et al., 2016). SLR employs a specific methodology of collecting and analysing data from the existing literature (Harden & Thomas, 2005), by correlating data with conclusions to clarify what is known and unknown (Xiao & Watson, 2019). Along with this paper, two separated research streams have been analysed in order to aggregate knowledge and to identify common patterns on the interaction between AI and HRM (Borges et al., 2021; Macke & Genari, 2019).

In this piece of research, authors have followed suggestions offered by Fisch and Block (2018) and Thomé et al. (2016) to conduct an SLR. These authors highlighted the most relevant issues to be considered in every SLR:

1 focus on the topic and state of the research questions.

2 locate and recognise the relevant literature, particularly related to the research questions, systematically.

3 choose the right balance between breadth and depth in setting clear selection criteria able to identify all relevant studies but focusing only in the description of the most relevant ones.

4 break down research into relevant portions and create consistency between them in order to focus on relevant concepts.

5 derive meaningful conclusions, including a summary of the review.

The first stage has been indicated in the previous section of this paper, where the main aim of this piece of research has been shown and the research questions have been posted.

In order to undertake Stage 2 and to, therefore, locate and recognise relevant literature related to the research questions, scientific keywords and terms linked with the research questions were identified. These keywords and terms have been carefully selected to identify qualified articles in the research field (Balaid et al., 2016). Based on the recommendations Örtenblad (2010), incorporating similar terms to AI and HRM offers flexibility to collect relevant articles, regardless of whether AI and HRM are explicitly mentioned or not. To do so, VOSviewer was used to measure the relatedness and association strength of the terms. In particular, the words of AI and HRM were written in Scopus databases. To maintain the quality of this piece of research, books, reviews, case reports, editorials, data papers, abstracts, meetings, conferences and working papers were excluded due to the limited peer-review process (Nolan & Garavan, 2016). Furthermore, English language was selected for both conceptual and empirical articles.

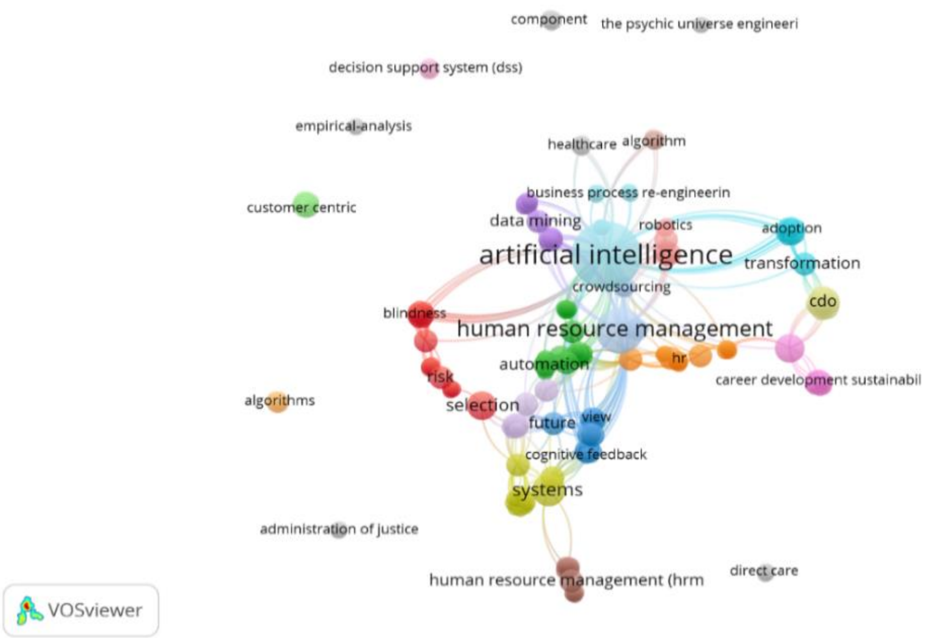
Results

Following the guidelines mentioned in the previous section the first bundle of articles, considering the set pre-requisites, were retrieved. In order to better select the most relevant articles to be analysed dealing with the researched topic, the preliminary list of articles were processed in VOSviewer to extract all the derivative keywords. This mechanism was used to identify the degree of relatedness between terms on a map. The relatedness was determined by the ratio of the co-occurrence between terms over the product (van Eck & Waltman, 2017), to better identify the final keywords to be used in the final searches performed in Scopus databases (see Figure 1).

Table 1: AI and HRM selected Keywords combinations (First article)

AI (Artificial intelligence) + HRM (human resources)					
HRM term			General AI term		
Recruiting	**Development**	**Performance appraisal**	**AI Applications**	**AI units**	**AI definition**
Selection	Professional career	Performance review	NLP: natural language processing (text mining)	Machine Learning	Big data
Job posting	Promotion		Expert system	Deep learning	Data Mining
	Career development		Robotics	Neural network	
			Machine vision	Predictive analytics	
			Speech (chatbots)		

Figure 1: Image of the VOSviewer network visualisation of the AI and HRM map (see online version for colours). (First article)



Afterwards, all the keywords that had been generated by VOSviewer, together with some others from the HRM definition of Armstrong and Taylor (2020), and the explanation of AI by Salehi and Burgueño (2017), were considered for building the keywords table (see Table 1). Armstrong and Taylor (2020) define HRM as the way that people are managed, evaluated, developed and employed in an organisation, while Salehi and Burgueño (2017) refer to deep learning (DL) and ML as the basic building unit of AI supported by big data.

It is important to highlight that, as a result of this preliminary analysis, not all HRM practices were selected for this study, but the scope of it has been limited only to recruiting, developing employees and performance appraisal which are directly linked with the AI keywords generated in VOSviewer. AI was researched only in terms of AI definition, AI applications and AI units as a result of the keywords generated by VOSviewer.

By following this process, the final keywords used in this SLR are shown in Table 1. These terms were combined both alone and with the general search terms. For each individual subject area, search terms were concatenated with the general search terms.

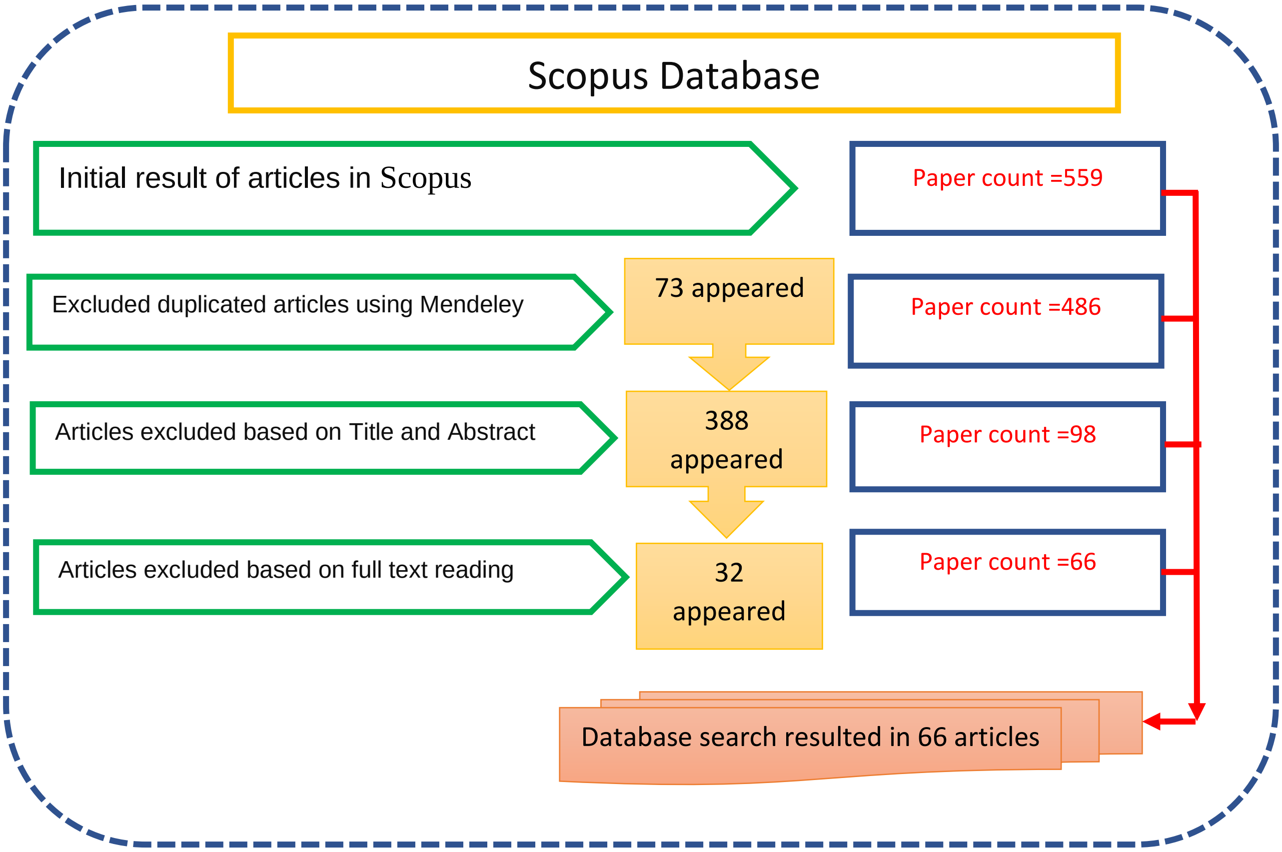
Starting from the identified keywords, the SLR was undertaken. The selection criteria of the literature included in this study is summarised in Table 2. It should be highlighted that, by using VOSviewer science mapping, a topic map of the AI and HRM fields is provided. This topic map can be used to examine the intellectual content and structure of AI and HRM in rich detail (Markoulli et al., 2017).

Table 2: Selection criteria of the literature (First article)

Characteristic	Criteria
Source	Scopus-Elsevier, Science Direct-Elsevier
Period	From 2010 to May,2020
Language	English
Publication medium and research areas	Scientific Journals related to management (specifically HR) and AI, and listed in the following research areas: Recruiting, Development, Performance appraisal, AI Applications, AI Building blocks and AI definition.
Content	Articles related to the research questions. Books, reviews, case reports, editorials, data papers, abstracts, meetings and conferences were excluded
Research design	Empirical or conceptual
Method	A scientific analysis in the title of the articles, abstracts and keywords using Mendeley as a tool

Considering all the terms in Table 1, searches were conducted. On the one hand, HR in detail with all the AI terms were searched; and on the other hand, AI with all the HRM terms. These combinations generated 559 articles (searches strategies can be found in Appendix 6). Results from this primary study contained articles from different scopes and not limited to, for instance, recruiting, natural language processing (NLP), text mining, ML or DL.

Figure 2: Research strategy and study selection process (adapted from Giuffrida and Dittrich (2013)) (First article)



In the next stage, the most relevant literature works of these 559 initial papers were screened by checking their compatibilities with the selection criteria to ensure relatedness and strength, and to synthesise the reported results. Furthermore, 73 duplicated articles were excluded by using Mendeley (Thomé et al., 2016). As a result, 388 articles were excluded due to their incompatibility in their titles and abstracts with the research scope and research questions. At this point, 98 papers were examined based on full-text reading. They met the inclusion and exclusion criteria that are often used in similar research papers (Balaid et al., 2016; Cooke et al., 2019). Finally, only 66 papers were selected as those that met all the criteria set in this SLR. Appendix 7 includes details of these finally selected papers. Figure 2 summarises the research strategy and paper count during the paper selection process.

All these 66 papers were analysed according to three complementary aspects related to research questions, namely: general AI concept in the HRM context, AI applications in HRM and adoption strategy of AI in HRM.

Considering this classification over the final list, it should be noted that 'general AI concept' in HRM concerned 51% of all the whole samples (N = 34/66, 51%). 'AI applications' in HRM concerned 49% of all the sample (N = 32/66, 49%), while 'adoption strategy' of AI in HRM concerned the whole sample. As for the type of study conducted, it was noteworthy that most studies into 'general AI concept' in HRM took a qualitative approach (N = 22/34, 64.7%) and very few followed a conceptual approach (N = 10/34, 29.5%), while the quantitative approach studies covered 5.8% (N = 2/34 = 5.8%).

In terms of 'AI applications' in HRM, studies were distributed among a qualitative approach (N = 17/32, 53.1%), a conceptual approach (N = 7/32, 21.8%) and a quantitative approach (N = 9/32, 28.1%).

Finally, another aspect worth highlighting is the fact that AI in HRM context is quite a recent research field, and prominently 95.5% of Scopus studies have been published in the last five years, between 2015 and 2020.

Discussion

In the following subsections, target papers are analysed and summarised. Knowledge has been structured to answer the set research questions.

The general AI concept in the HRM context

Inadequately understanding of AI potential in HRM is seen by HR managers and academics as one of the main reasons causing lack of standardisation in AI definition in HRM, and holding back advancements within this field (Arco et al., 2019; Kaplan & Haenlein, 2019). However, AI plays a vital role in shifting HRM practices to become enterprising in the digital era (Abdeldayem & Aldulaimi, 2020). As technology is everywhere and it is changing the way business works (Prem, 2019), HRM practices have also been affected by emerging digital technologies like AI, networks and robotics (Black & van Esch, 2020). These technologies, along with big data analytics, the IoT and virtual reality, are shaping the future of the workplace increasing its efficiency and competitiveness (Bhattacharyya & Nair, 2019). This fact makes HR managers to combine HR practices with AI technology to assess the successes and failures of HRM strategies (Sahota & Ashley, 2019).

Researchers have analysed AI in HRM context by several approaches, which have increased the fuzziness of HR managers to understand AI within this context. Some of them refer their studies to AI definition from a general point of view, most of them are technical and technological definitions. While others focus on the advancements made to AI in HRM.

Among other definitions, AI is defined as a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation (Kaplan & Haenlein, 2019). Also, AI is defined as science, engineering and technology with emphasis placed on intelligent behaviour, mimics the human capabilities of thinking, sensing and reacting (Gherghina, 2015). It has also been seen as a technology of machine (engineering) information processing that mimics the cognitive activities of humans (Popkova & Sergi, 2020). Therefore, AI is associated with the technologies of big data (Arco et al., 2019) and smart sensors (Bailey & Barley, 2020) that have a tied relation to HRM.

AI consists of ML and DL (Lee & Shin, 2020), both of which are computer science fields that derive from AI (Engström & Strimling, 2020). ML is a collection of algorithms that:

a learn

b predict and analyse based on stored data

c optimise basic utility functions under uncertainty

d extract hidden structures from data

e categorise data into concise descriptions (Kim J. , 2019)

On the other hand, ML is deployed mainly when computer processors and storage devices are sufficiently advanced, and it uses data to generate statistical codes (Kim J. , 2019). DL is considered a subset of ML that depends on employing a complex structure with many nodes, hidden units and learning algorithms, and are expected to be at the centre of ML (Lee & Shin, 2020). Furthermore, DL uses neural networks in some high rich data contexts that brought users closer to true AI (Wang et al., 2018), which represents the ability of technology to mimic interactive human decision-making (Tambe et al., 2019). Identifying the sophisticated functions of ML and DL will recognise the core momentum of data into transforming HRM which are brought by recent advances in AI (Lee & Shin, 2020), this momentum and new methodology in managing data shows a new approach in understanding and defining AI in HRM (Garcia-Arroyo & Osca, 2019).

As far as AI advancements in HRM concerns, academics have identified diverse breakthroughs that can be grouped into four types. The first one highlights how AI works to reduce the costs of the products and services being offered to employees (Bhattacharyya & Nair, 2019; Moore, 2020), for example, AI can enhance the competitive advantage of companies by reducing the cost of the services offered in HR departments by between 20% and 25% (Lee & Shin, 2020), e.g., selection and recruitment, performance evaluation and talent management (Huang & Rust, 2018; Masum et al., 2018). In addition, AI allows employers to process information of their employees and potential employees (Ali & Frimpong, 2020; Vinichenko et al., 2019; Zhang et al., 2021). For instance, AI enables employers to collect data about employees from social media, platforms and intranet, and far away from humans' ability to absorb, interpret and more efficient (Campbell et al., 2020; Chang & Yeh, 2018; Hilbert, 2016).

Secondly, it also facilitates the creation of new knowledge by linking employees' information and ERP systems to integrate previously fragmented information flows (Masa'deh et al., 2019; Osuszek et al., 2016). Thirdly, AI has the capability to take over employees' routine work, which extends the intellectual work of humans by emphasising the remote and flexible workplace (Todolí-Signes, 2019). Lastly, AI enables HR managers to learn from data and to rule out assumptions attached to statistical methodologies, which offers valuable and automated solutions to problems (Campbell et al., 2020; Kim et al., 2020; Berhil, et al., 2020).

Both approaches (AI definitions & AI advancements) are considered a challenge for HR managers in fully understanding AI concept in HRM. Harmonising dispersed definitions of AI and AI advancements in HRM would facilitate the role of HR managers in overcoming the criticalities of AI in HRM (Abdeldayem & Aldulaimi, 2020). On the other hand, standardisation would facilitate the comprehension of concepts such as big data analysis, IoT, cloud computing, virtual reality, cybersecurity, collaborative robots, or machine-to-machine communication by academics in HR and managers in general. It should be noted that these terms represent a basis on which future HR jobs need to be developed (Jerman et al., 2020).

Therefore, as a result of this analysis of existing literature, the following AI definition in HRM is put forward. Appendix 5 shows the references used to support the definition raised as a result of this piece of research. AI in HRM can be seen as a technology that consists of ML and DL which are able to mimic human cognitive activities to achieve HRM practices. This conclusion can maintain competitivity in today's global economy by looking at ways that incorporate AI for HRM into their decision-making process. Organisations should collaborate and rely on AI to perform administrative duties (Jarrahi, 2018), so that HR area becomes more efficient (Ferràs et al., 2020). Adopting AI in HR practices can help to reduce HRM time spent on administrative tasks by providing added value answers to routine queries, such as recruiting process, retention and measuring the return of investment (Popenici & Kerr, 2017). Furthermore, it is expected that the impact of AI in HRM will go beyond changing the nature of the workplace, causing changes in economic mechanisms and business models, which will potentially bring impacts to the organisation (Abdeldayem & Aldulaimi, 2020).

AI applications in HRM

As stated in previous sections, another challenge that affects HR managers' AI knowledge is the large number of applications in the HRM context with no clear adoption strategy. Researchers argue that AI technologies bring about some radical changes to the way HRM practices influence business operation in organisations (Nawaz, 2019; Trocin et al., 2021). Thus, AI has begun to reflect on employment patterns and the way companies deal with, but without limiting, staffing, managing employee performance and employee development (Michailidis, 2018). This results in shifting HRM practices to a great extent. Therefore, AI is the buzz word in companies and specifically in HRM. It completely transforms HRM practices by producing an easier way of hiring and innovative solutions for a high number of issues (Bafna et al., 2019; Chakraborty et al., 2020).

Some of the analysed research articles refer to a specific AI application in HRM practice, but do not consider other AI applications. For instance, Chung and Chen (2021) explore the role of text mining in analysing the core competencies of HR professionals by collecting data from advertisements and HR agencies depending on AI. Moreover, Shanmugam and Garg (2015) refer to AI as a tool to minimise the appraisal bias and to support both employees and management to understand the progress and shortcomings of an individual's performance. Furthermore, Padmashini et al. (2018) highlight vision-based algorithms using DL when managing human resources. In contrast, this research work highlights the extending role of AI to intellectually handle the demanding tasks that require a degree of autonomy without human intervention (Willcocks et al., 2017; Xu et al., 2020) by grouping the most common applications of AI into HRM as follows.

Based on the assumption of Strohmeier and Piazza (2015), AI applications in HRM have been classified into six scenarios:

a candidate search with knowledge-based search engines.

b résumé data acquisition with information extraction.

c self-service with interactive voice response.

d HR sentiment analysis with text mining.

e staff rostering with genetic algorithms.

f employee turnover prediction with artificial neural networks.

All these scenarios are related to the three HRM practices considered throughout this paper as follows: scenarios a, b, c and d are directly related to recruitment and development. And scenarios e and f are related to performance appraisal. The following subsections deal with applications that are harmonic with previous scenarios.

Below, AI applications included within the analysed literature and related to the six aforementioned scenarios have been analysed.

As far as candidate search is concern, it can be noted that this search run with knowledge-based search engines is considered as one of the main pillars of AI in HRM (Chakraborty et al., 2020; Lochner & Preuß, 2018). They involve digitising recruitment and assessment methods, also known as e-recruiting. Generally speaking, recruiting refers to the provision of employees' quantity and quality that are necessary for business (Strohmeier & Piazza, 2015). This practice implies numerous subtasks, such as the planning, selection and onboarding of new employees (Michailidis, 2018). These tasks can be moved to AI-enabled recruiting thanks to AI technology. Today's candidates increasingly spend time in digital spaces due to the influence of AI tools on recruiting, especially in the early stages (van Esch & Black, 2019). According to Geetha and Reddy (2018), advantages of AI in recruitment can be summarised as five main aspects:

1 AI saves time by keeping records, which avoids repeating events.

2 AI assists HR in acquiring the best talent required by the organisation (Daramola et al., 2010).

3 costs are saved not only by acquiring the right candidates but also by reducing the cost of outsourcing recruitment agencies (Kundhavai et al., 2020).

4 AI tools depend on big data analyses, which are initiated for unbiased screening and selection during the recruitment process (Wang et al., 2018).

5 loyalty and trust between candidates and organisations increases, thanks to the interactive communication between them.

Résumé data acquisition with information extraction refers to ML that provides machines with access to data and allows them to earn for themselves (Lee & Shin, 2020). Rąb-Kettler and Lehnervp (2019) go deeper in explaining the role of AI in résumé acquisition by identifying the role of ML, which is able to:

a design a job description for a vacant position.

B CVs screening by identifying keywords and placing candidates in the right opening positions.

c pre-onboarding, such as automated welcoming activities.

d finally, scheduling and interviewing a candidate with a chatbot that will easily replace a human interviewer (Kundhavai et al., 2020).

Chatbot is explained as an AI technology that simulates human dialogue for not only answering employees' questions, but also as a coaching, facilitator and personal employee supporter (Kamal et al., 2018). Chatbots are seen as career planning aids that, for example, they can help users to interpret assessment results, check their progress based on collecting career data, and assisting in comparing different career options. Many users may like the convenience and on-demand availability of chatbots despite knowing that the personal attention they receive is not provided by a person. Thus, such technological support may assist with some routine aspects of HR practices, while HRM focus on helping with a particular decision that reflects directly on the company's future (Lent, 2018). Robots are another approach of a chatbot that works on interviewing and selecting candidates, learning, communicating, and even controlling harassment, depending on NLP and pattern recognition (Stanley & Aggarwal, 2019).

Regarding self-service with interactive voice response, the literature explains that it forms a part of AI applications that respond to users' questions and prolongs conversation with them (Pradana et al., 2017), which could improve the interaction and effectiveness of e-communication (Biswal et al., 2020), and likewise, a channel of interaction between humans and computers via voice. Such voice-based interaction could allow the human voice to interact with his/her request with no direct human intervention. This feature could be implemented in employee self-service (ESS), which could employ interactive voice responses for HRM services (Strohmeier & Piazza, 2015). Depending on recognising employees' natural language, it could be intelligent enough to remember the user's name, position and frequent questions that they use to ask (Pradana et al., 2017).

HR sentiment analysis, also called opinion mining, aims to analyse employee sentiments, opinions and attitudes towards different elements like the organisation's services and products (Khan et al., 2016). The opportunity to identify the divergence of opinions about the corresponding entity (product, service, decision, event) enables the stabilisation, revision, improvement or withdrawal of that entity to maintain receiver satisfaction (Krishna & Devi, 2021). Exploring sentiments of employees, managers, applicants and further HR stakeholders about many HRM-relevant practices, such as compensation ratios, career possibilities, training quality, management and leadership style, could constitute valuable information on the strengths and weaknesses of HRM (Patel & Jha, 2015). Such opinions and sentiments about the workplace and employers are increasingly expressed in social networks and web-based documents (Strohmeier & Piazza, 2015). Another way to investigate employee opinion is the text mining technique. It is a method that bridges the gap towards information retrieval, document classification, information extraction and terminology extraction (Lucini, et al., 2017). This tool is used to identify employees' reviews of their companies and to identify job satisfaction (Jung & Suh, 2019). Text mining can also analyse sentiments by combing NLP and data mining techniques. It concentrates on identifying an opinion or sentiment by using the ML algorithm (Khan et al., 2016).

As for staff rostering with genetic algorithms, the literature that deals with this topic is somewhat limited. Strohmeier and Piazza (2015) address this technology as a monitoring tool to generate optimal assignments of employees to determine if the qualitative and quantitative requirements of tasks match employees' skills and abilities. While van Esch et al. (2021) couple biometrics and genetic algorithms with AI technology to monitor the data generated from, for instance, fingerprints, facial (Dong et al., 2020; Kamal et al., 2018) and voice recognition, and wearable devices that can create biometric curriculum vitae. Moreover Suen et al. (2020) apply the AI-based decision agent with biometrics, which enables an automatic interview platform to be developed.

An artificial neural network is another AI application in HRM that is based on the category of discovered knowledge which leads to solve, cluster, classify, estimate and predict tasks (Biswal et al., 2020). This tool works to predict employees' turnover through which they are likely to leave and to also uncover unknown factors that influence turnover (Strohmeier & Piazza, 2015). This can be utilised by HRM to determine what their turnover rate is, and who is likely to leave the company. Identifying these individuals and attempting to increase their satisfaction with the company will enhance competitive advantages. Furthermore, artificial neural network programs can also list common complaints and solutions related to those employees, as well as possible outcomes of all the solutions to these issues (Dickson & Nusair, 2010).

Adoption strategy of AI in the HRM context

As far as AI adoption concerns in the HR context, as a result of unclear AI solution business models (Prem, 2019), managers face high uncertainty on the decisions to be taken (Strohmeier & Piazza, 2015). Some researchers identify critical success factors in order to implement AI. For instance, Kim J. (2019) claims that a successful AI implementation plan in a company should include top management decisions, organisation and human resources, infrastructure for the AI system, end-users support and a company strategy. Along similar lines, Huang and Rust (2018) develop a theory of AI job replacement that depends on four bits of intelligence required (mechanical, analytical, intuitive, empathetic) to decide between humans and machines to accomplish tasks. Both these examples although deepen into AI implementation, they do not consider specific AI adoption strategy in HRM.

It should be noted that only two papers, among all the papers covered by this SLR, include recommendations about adopting an AI strategy in HRM. However, they do not cover all HRM practices but just part of them. In particular, these papers deal only with recruiting. Firstly, Black and van Esch (2020) identify five specific recommendations to deploy AI recruiting tools:

a) Identify critical positions: Companies can identify important talent categories and apply AI-enabled tools to these limited groups of job candidates.
b) Take care to corral: If there are accidental biases that were available at the organisation in the past, it is necessary to deliberately neutralise them and allow for AI system to manage them.
c) Build an integrated system: Companies offering AI solutions while recruiting should focus on providing end-to-end solutions that are not only efficient and effective but also enjoyable for candidates.

d) Be transparent and upfront: AI-enabled recruiting systems are less biased and more objective than humans. Employing and acknowledging the use of AI in recruiting allows a company's brand to be seen as cutting-edge.
e) Be human: Humans need to conduct end interviews with candidates. Candidates seek and need a chance to determine if they like the company culture in which they will work and the people with whom they will work.

Second van Esch et al. (2021) explain how managers can design, deploy and market AI-enabled recruitment activities: firstly by focusing on the positive aspects of AI-enabled technology; secondly by considering the ecosystem of digital, physical and social realms that are representative of potential candidates' experiences in a service delivery context; thirdly, trendiness as an important boundary condition in AI-enabled recruiting; fourthly, highlighting the relation that links trendiness, biometrics and social media usage in outcomes, such as the job application likelihood.

In terms of human resource development in AI, no papers have been found considering a clear adoption strategy for AI. In contrast, an attempt is made by Shanmugam and Garg (2015) to develop an intelligent IT system to address the issues of biases in employee appraisal systems by reducing human intervention to a minimum.

Conclusions

The purpose of this article was to evaluate what is known about AI in HRM within an academic context via a SLR. The literature review was based on guidelines of previous systematic studies (Balaid et al., 2016; Cooke et al., 2019; Thomé et al., 2016). AI technologies have been prominently placed in contemporary organisations. On the other hand, high inspirations are connected to the organisation competitive paradigm.

Generally speaking, AI in HRM context and AI applications in HRM have increasingly drawn the attention of HR managers and academics. However, AI in HRM is an emerging technology that faces several challenges such as data security, privacy, and other economic aspects (such as the cost of technology and the cost of the implementation) which need to be extensively studied to discern the future of this technology.

In order to analyse AI in HRM in detail three research questions are set:

1 How has AI been conceptualised and generalised in the HRM context to date?

2 What is known about AI applications in HRM?

3 How these applications have been adopted so far?

In order to answer these questions, the status of AI in HRM has been reviewed. Five hundred fifty-nine articles published between 2010 and 2020 have been identified, while 66 papers were selected as those that met the criteria set in this SLR.

As far as the first research question concerns, the authors offer a complete definition of AI in HRM. This definition is built based on the existing literatur and it takes into account two approaches: previous AI definition and advantages of AI in HRM.

Regarding AI applications in HRM, it is shown that they are gaining momentum (Abdeldayem & Aldulaimi, 2020). However, research oriented towards HRM practices is still unclear due to the fact that the adoption strategy of AI applications in HRM is not clear yet. Therefore, this SLR identifies the most frequent AI applications in HRM such as ML, NLP and artificial neural network that bring radical changes to the way HRM practices influence the business operation in organisations. However, the literature fails to build a clear framework for adopting these applications in HRM. In parallel, some researchers attempt to offer recommendations to deploy some portions of HRM practices. We found that recruitment is mature enough in the literature, while development and performance appraisal still need to be studied in more detail.

With respect to theoretical implications, the findings showed that the use of AI in HRM has not been all-around investigated by researchers yet, in spite of digital strategies to offer strategic benefits of AI in working with people contexts. While this paper demonstrates the usage of AI in HRM to some extent, the findings suggest that this context has been little discussed so far by academics and still poses unanswered issues and concerns.

This literature review contributes to the literature by building a clear definition for AI in HRM and goes along with the finding of Bondarouk et al. (2017) who claimed more theoretical analysis before empirical research is vital for practical adoption. Align with that, identifying a framework of adopting AI applications in HRM, bring integration of human resources and business strategies at the organisation's high level of decision-making, as well as comprehensive perspectives into the potentials of AI applications for HR practitioners (Jatobá, et al., 2019).

Moreover, given the ascent of AI in the digital age, there are still gaps in order to examine the formulation and implementation of the new age of AI. Through identifying a comprehensive framework for setting adoption strategies of AI in HRM, especially, how AI transforms a wide range of HRM practices

As far as managerial implications concerns, the outcomes of this paper can be a foundation for a useful and needed manual for management and HRM practices, requesting new ways of work, more efficient and aligned to the new digital era. Besides, the exhibit of the AI in HR can assist managers in receiving these new advancements with more noteworthy mindfulness about the opportunities, difficulties and advantages that AI may provide to their businesses.

Limitations and future research

Despite our efforts in identifying the papers supporting the topic under study by following an accurate methodology in the analysis, this piece of research includes some limitations. For instance, although we decided to exclude books, reviews, case reports, editorials, data papers, abstracts, meetings, conferences and working papers, given the limited peer-review process (Nolan & Garavan, 2016), we are aware that some of them could have offered relevant contributions, especially due to the novelty of the topic studied in terms of applications and adoption strategies of AI in HRM. Despite these limitations, this paper is the first to attempt to provide a comprehensive picture for an AI definition in HRM, AI applications in HRM and existing AI adoption strategies in the HRM context. Therefore, one of the contributions that this review makes is to investigate the adoption strategy of AI in HRM while pointing out that further research is necessary in that particular field.

Building on this piece of research, new lines for future research could be opened, such as identifying a comprehensive framework for setting adoption strategies of AI in HRM. A wide range of different HRM practices could be analysed including, but not limited to, retention, staffing, compensation and managing employee development as another research field (e.g., 'What is the adoption strategy of AI in HRM that covers all HRM practices?'). Another research line interesting to be developed, based on the conclusions of the present study, is the analysis of the success factors that impact AI adoption in HRM. On the other hand, the analysis of the added value offered by the implementation of AI in HRM compared to previous technologies would help managers in the decision-making process about digital corporate strategies.

Along these lines, it is essential to examine how leading companies implement strategies to exploit the AI potential within HRM changing, AI-human condition for producing business value.

4.2 Article 2: "Perspectives of Indian HR professionals on AI-powered chatbots in recruitment: multiple cases"

Title:	Perspectives of Indian HR professionals on AI-powered chatbots in recruitment: multiple cases
DOI:	---------
Format:	Journal Article
Journal:	German Journal of Human Resource Management
Language:	English
Journal Metrics	Scopus, Q3 . Cite Score: 1.5
Status:	Under Review
Keywords	Artificial intelligence; human resource management; chatbots; recruitment; India.

Abstract:

Although artificial intelligence (AI) is broadly extended worldwide, however, full potential is not being reached in human resource management (HRM) so far. In fact, there is still a gap in covering the adoption of chatbots in recruitment paying particular attention to the Indian market. A qualitative analysis has been undertaken in selected Indian companies. One of the main conclusions drawn from the study, there is a gap between what are Indian IT companies offering for recruiters and what are recruiters know about the latest development of the chatbots in the Indian market. As a practical implication, chatbots have several features and limitations. On the one hand, facilitate the job of recruiter. On the other hand, chatbots for hiring a mid-level and senior-level are not useful. The paper provides an extensive analysis for HR managers and academia of the usefulness and limitations of chatbots in the recruitment process in India.

Introduction:

Many of the changes occurring today, and perhaps much more so in the future, will be driven by emerging technology and increasing access to human resource (HR) data (van den Heuvel & Bondarouk, 2017). Artificial intelligence (AI) plays a singular part in the emerged technological revolution that takes part in our organizations. It does not only transform organization activities, but also the way of organization attracts and assesses potential employees (Flanagan & Walker, 2021; Magistretti et al., 2019). Moreover, it increasingly forms an essential context for the performance analysis and distribution of manpower within workplaces driven by data generated from AI applications (Flanagan & Walker, 2021).

AI refers to the big umbrella of computer science that allows the performing of human tasks including human intelligence (Zhu et al., 2021), decision making, analysing data, and recognizing the pattern of speak-visual-interpret (Bongard, 2019). AI has reached all organization areas including customer service, finance, production, and human resource management (HRM) (Kitsios & Kamariotou, 2021; Magistretti et al., 2019; Strohmeier & Piazza, 2013; Ziebell et al.,2019). It should be noted that, although AI began as a field of research in the 1950s (Jatobá, et al., 2019), it was not widely extended until the current so-called industrial revolution 4.0, as an evolution of the digital age. This development is affecting many areas of organization, including recruitment processes (Rhemananda et al., 2021). Paying attention to the HRM area, although HR managers are witnessing of growing technology–human interaction (Bondarouk & Ruel, 2009), AI full potential is not being reached in HRM functions, particularly in recruitment (Kshetri, 2021). According to comprehensive research conducted by the Boston Consulting Group, the recruiting function has the most significant influence on firms' revenue growth and profit margins when compared to any other function in the field of HRM (Sullivan, 2012). Indeed, improper hiring decisions can result in not just underperforming employees but also fast employees resignation. High turnover may have a direct impact due to employee replacement costs (e.g., interviews and rehiring fees, training and productivity loss, overtime of other workers), as well as indirect impacts such as poor customer service or a drop in staff morale (CIPD, 2016). Thus, improving organizational recruiting procedures via employing the best candidate has a significant influence on organizational performance (Pessach, et al., 2020).

Recently, organizational's recruiting is linked with the technological revolution, which has triggered major efforts to attract qualified candidates (van Esch et al., 2021). Therefore, technology-human interaction is currently reshaping the functionality of the recruitment process from a necessary HR task to a major strategic concern for companies (Black & van Esch, 2020). The value and efficiency of such technology–human interaction is increasing as a reason for moving the technological revolution from just big data to machine learning, or even beyond, to AI (Nawaz, 2019). AI-enabled chatbots in recruiting systems have evolved from nice to talk about to necessary to utilize (Black & van Esch, 2020).

Chatbots can be used as an AI-based recruitment tool, which is utilised to interact with the candidates to facilitate the recruitment process (Kulkarni & Che, 2019). It is noteworthy that chatbots do not act just as an employees' serving tool but enhance learning by changing the perspective from 'organising' knowledge and expertise of employees to 'servicing' them (Flanagan & Walker, 2021). Minimizing the cost and Job displacement will always be a motive for the employer to invest in AI (Upchurch, 2018). However, there are still a lot of barriers to overcome, and the technological singularities of robots and chatbots are still far from imminent (Upchurch, 2018). In fact, despite multiple apparent advantages, surveys showed that CEOs and other senior executives are delaying in embedding AI-powered tools (as it could be chatbots) due to, among other reasons, an ambiguous vision of the usefulness of chatbots in recruiting and the reflection on employee's performance (Bughin et al., 2019).

E-recruitment and more specifically the use of AI in conjunction with the analysis of employee performance resulted from adopting chatbots in recruitment, is the subject of very limited literature. This area is not mature, evolving quickly, and relatively unstable (Allal-Chérif et al., 2021). For this reason, this paper tries to analyse the current situation of chatbots' implementation in recruiting and the reflection of this technology on employee's performance. Paying particular attention to the Indian market. The study is based on data retrieved from interviews with professional experienced recruiters among a group of the largest Indian companies, which are adopting advanced technology in recruiting. This study is one of the first papers analysing the advantages and drawbacks of chatbots' implementation for an AI-powered solution in HRM at the Indian market, one of the world's most advanced in-tech developments according to the Stanford AI index 2021 (Saxena, 2021). On the one hand, it contributes to enhancing AI knowledge in HRM from an academic point of view. On the other hand, it offers background and reference for recruiters and HR professionals to consider the status of chatbots in the recruitment processes and the reflection on hired employees' performance.

This study is organized as follows: first, it discusses the practical and theoretical context of AI, recruitment and chatbots. Then, the research methodology and data collection are explained. Next, case studies and interviews are examined and discussed. Finally, research conclusions are summarized.

Literature Review

Artificial intelligence-powered chatbots in recruiting

This section is intended to provide an in-depth look at what is currently known about chatbots in recruitment. For this purpose, a brief review of literature has been carried out to identify relevant academic studies in this area. Furthermore, technical reports on HRM, AI and recruitment have been considered. The main keywords selected and used to cover complete literature include artificial intelligence, human resource, chatbots, employee performance and recruitment.

AI is one of the most ambitious technological developments that is able to mimic humans in terms of thinking and performing tasks that usually require human intelligence (Canhoto & Clear, 2020; Lexcellent, 2019). In the last five years, a growing body of literature has examined AI and its applications. Some of the most studied aspects found in the literature are AI-algorithms, big data and cloud computing. It has been shown that the central role of AI is to correctly interpret external and internal data in order to derive information and knowledge (Frey & Osborne, 2017; Wamba et al., 2021). It should be noted that academics have paid attention to AI within the context of industrial revolution 4.0 due to their uncountable possibilities of automated cognitive tasks (Frey & Osborne, 2017). Optimists believe that thanks to the symbiosis between human and AI; AI will soon help to improve our lives every day (Paschen et al., 2020).

Today, AI is reshaping companies' ways to facilitate workforce planning, which reflects on overall productivity and employee performance. AI has an impact on staffing, talent acquisition, training, performance appraisal and succession planning (Jarrahi, 2018).

The use of AI in the recruiting process has been placed at the heart of this transformation (Black & van Esch, 2020) . One of the most time-consuming activities in HR is the recruiting process. HR professionals invest a lot of time in order to select the right candidate. Traditional recruiting implies physically screening CV, assessing applications, scheduling and conducting interviews (Chapman & Webster, 2003). However, from the lens of digital recruiting 3.0, employers could take advantages of today's technology by adopting AI in recruitment. These advantages would enable recruitment officers to perform recruitment activities more quickly, more efficient and hence reducing costs in the overall process (Vardarlier & Zafer, 2020).

Moreover, enrich HR professionals' role in adding strategic value for the organization (Lee & Shin, 2020; Upadhyay & Khandelwal , 2018).

The core advantages of AI in recruitment come from AI's ability to digest data and make decisions at mass and rates far above human capabilities (Black & van Esch, 2021). For instance, information of potential candidates could be extracted from LinkedIn, Facebook, Instagram, Pinterest, and Twitter, then matching this essential information with job requirements (Campbell et al., 2020).

Recruitment is traditionally the first step in building and structuring an organization (Acikgoz, 2019). It involves efforts aimed at attracting bright candidates who meet the organization's requirements (Vardarlier & Zafer, 2020). It should be noted that recruitment is also a key factor for organizational performance and corporate strategies since it affects corporate brand and production level (Kim et al., 2011). The recruitment process is divided into three main stages: generating applicants, maintaining applicant status, and influencing job selection (Barber, 1998). Each stage informs others to ensure job description formulation, vacancy advertising, CV screening, and interview candidates (Chapman & Webster, 2003).

The review of a candidate's application and resume in HR processes is called the pre-screening of candidates (Vardarlier & Zafer, 2020). In this stage, based on the analytical data, pre-screening should be performed to assess whether the candidate possesses the necessary competencies for the position, as well as the required skills and experience (Grabara et al., 2016). The primary goal of the pre-screening process is to gather and analyse data for the next phases by determining the candidate's eligibility for the vacant position. The resulting data from the recruiting process is widely considered one of the most time and cost consuming in HR processes (Laumer et al., 2015). Furthermore, the determinant of employee performance in the future (Podgorodnichenko et al., 2020). Therefore, this activity is one of the most likely to be aided by a technological innovation aiming to reduce costs and time while maintaining or even enhancing the quality of data interpretation and conclusion.

Based on this proposition, current AI solutions have been screened, and chatbots are found to be a plausible solution to cover the aforementioned need (Black & van Esch, 2020). Analysing the current AI solutions available in the market, chatbots are nowadays one of the most popular ones (Hill et al., 2015). Chatbots are interactive, virtual agents and computer programs that engage in verbal interactions with humans (Nawaz & Gomes, 2019). This technology is a type of human-machine interaction as they are designed to interact with users through the usage of natural language based on AI advancement (Przegalinska et al., 2019). It's worthy for highlighting that, around 80% of customer services in companies are using or plan to use chatbots in the near future as an interactive tool in answering customer inquiries (Ashfaq et al., 2020).

Chatbots are adding a strong milestone in the recruitment process by identifying candidate experience, effective communication between candidate and recruiter, scheduling conversations , and even taking all candidate requirements before entering the organization (Albert, 2019). According to Black and van Esch (2020), AI-powered recruiting has been used in four main HR activities: outreach, screening, assessment, and coordinating. While chatbots are mainly considered an advanced technology in areas of coordinating and assessment (Vedapradha et al., 2019).

According to the McKinsey Global Institute (2017) report, adopting automation technologies could affect 50% of the world economy, or 1.2 billion employees. Where just four countries (China, India, Japan and the United States) account for over half of these totals (McKinsey, 2017). Therefore, AI-powered applications and services have quietly become widely available in several Indian business sectors (Darwish et al., 2020). Within this context, the Indian government had increased in 2018 the budget of AI, Machine learning and the Internet of things to accelerate the spread of AI applications across various sectors (AIMA, 2018).

HR activities such as recruitment are considered one of these sectors that gain momentum in the Indian market. For instance, the 'people strong' company developed the first Indian HR Chabot "Jinie". It acts as an employee's work assistance. At the same time, 'phenom people' company launched the "PhenomChatbot" that allows candidates looking for jobs (Mohan, 2019). According to a survey conducted in the Indian market in 2017, 65% of employees think technology will improve their job prospects and recruitment experience in the future (PWC, 2018). On the same side, 47% of participants felt that job automation within their sectors was likely in the near future, with partial automation and humans being retained for specific expertise (AIMA, 2018).

Having analyzed the current development of AI in HRM, and specifically how chatbots technology is gaining potential in many countries all over the world, this paper tries to cover the following gaps: How AI-powered chatbots are seen in India Market as a plausible tool for being used in HRM context and particularly in recruiting. Furthermore, the reflection on the hired employees' performance.

Research methodology and data analysis

Given the lack of deep knowledge in the field where the present study is framed, a qualitative approach has been selected in order to take a more holistic perspective on the analysis (Hesse-Biber, 2010; Patton, 2005; Saunders & Townsend, 2016). It has been seen that, especially in management research, qualitative approach is the most suitable when studying new (or not already studied in-depth) phenomena or testing perceptions and causal mechanisms (Bluhm et al., 2011). In particular, aiming at discovering and better understanding how firms are currently using chatbots in recruitment, case study methodology has been selected since it enables practical examination of new phenomena in a real-life context

(Rashid et al., 2019). The methodology used for data collection was expert interviews. This technique was used to record interviewees' ideas, views and attitudes (Ketokivi & Choi, 2014). The selected samples are national Indian companies that have strong roots in the Indian market. These companies are selected based on two specific criteria: 1) using completely / partially AI-powered solutions in daily operation and 2) the number of employees that characterizes medium and large companies. To tap in the most relevant information, key informants of each company have been targeted in order to collect and analysis technology's adoption in recruitment. Therefore, senior HR managers were contacted. In case HR manager faced difficulties in providing us with sufficient details of specific knowledge required for this study. He referred us to the in-charge employees in adopting new technologies in recruitment (as it could be: recruitment manager, or recruitment officer). Number of interviewees are determined by saturation level which introduced by Glaser & Strauss (1967). They conclude that interviewing participants could be stopped if the information is repeated and the collection of new data does not shed any further light on the research (Glaser & Strauss , 1967). Accordingly, data is collected from five experts only to avoid repetitive and superfluous information. Descriptive information of the interviewees (5 in total) and the interview data is provided in table 1. This table includes anonymized position, title, company activities and chatbot solution that the company was using at the moment of the study. This information enables comparability of the interviewees but without revealing the identity of the interviewees (as it has been required confidentiality).

Table 1: Interviewee data (Second article):

Nu m.	Title / Position	Years of experien ce	Area of experience	Chatbot solution	Company activities	Interview style	Interview duration
1	Senior Technical Recruiter	15	Hiring people across different levels up to the director or senior manager in the IT industry	Planning to adopt in the short term (but not yet)	The company provides Food services and Support services to the business sector, healthcare sector, education sector, sports & leisure sector, and defense sector across more than 45 countries	Online interview (Via Zoom)	26 min.
2	HR Head – B2B E-Commerce	15 plus	Recruiting and data HR analytics	Crash: only for internal purposes	One of the top 60 Global retailer groups with retail outlets all over India	Online interview (Via Zoom)	21 min
3	CEO and ex VP-Head of	20	Analysing structured and	Planning to adopt in recruitment	Converting HR Data into organization competitive advantage using advanced	Online interview	22 min

	HR Analytics		unstructure d data in HR		analytics and AI solutions	(Via Zoom)	
4	Senior HR Manager	14 years	Artificial intelligence, robotics process, automation, chatbots	Planning to adopt in recruiting	Digital recruitment and Data analysis solution	Online interview (Via Zoom)	20 min
5	Global Head of Talent acquisition	17 and half years of experienc e	AI in talent acquisition	The initial stage in adopting chatbot in recruiting	A multinational company supporting business to grow through using data analytics and data-driven solutions	Online interview (Via Zoom)	24 min

The interview questions were developed based on the pros and cons of recruiting chatbots from Indeed (2020), in order to cover new trends of chatbots in recruitment, moreover, reflect what is going on in the business field in academia (Myers, 2019).

Research has been designed covering two steps, which were conducted in series in order to analyse chatbots in recruitment from a different perspective. These steps started with a pilot study, conducted to find issues and barriers regarding recruiting emerging technology in recruitments. Later, a pilot of the questions was tested with three respondents working in intelligent recruiting and amended following their feedback (Kim Y. , 2010). The second step consisted of semi-structured expert online interviews. The interviews were carried out based on interview guideline questions resulting from the previous step (see Appendix 9) (Leech, 2002).

To increase the value of the findings, we adopted Braun and Clarke (2006) phases of thematic analysis in order to identify, analyse and report patterns (themes) within data. Interviews were verbatim transcribed from audio records. The resulting texts were coded. Codes were assigned to relevant information and comments mentioned during the interview (Weston, et al., 2001). Later, codes were reviewed and refined as the analysis progressed (Vaughn & Turner, 2016). The thematic analysis of the interview transcripts was browsed, coded and interpreted by using ATLAS.ti qualitative data analysis software (Paulus & Lester, 2016). After recognizing the main themes along with all the five transcripts, authors used ATLAS.ti to refine the specifics of the overall story and generate clear definitions and names for each theme. Finally, interpreted data, which then served as a vehicle for communicating our findings.

Case findings and discussion

The following subsections present the most relevant findings of this piece of research grouped thematically. It is worth noting from the outset that the implementation of AI-powered chatbots in recruitment in the Indian market is still in an emerging stage, and what the recruiter (user) is expecting from chatbots is not reflecting the real potential of chatbots within this context. However, it can be noted the growth in the accuracy of AI which makes chatbots more efficient and suitable in dealing with sophisticated incidents.

Chatbots in HR functions

According to interview data, it could be noticed that Indian HRM experts have separated between the potential advantages of chatbots from HR professional's perspective and candidate's perspective. These different views and perspectives could be attributed to different adoption levels of chatbots in HRM (Moeuf, et al., 2020). As far as the relevant features of chatbots from an HR professional's perspective are concerned, it can be pointed out, the advantages of chatbots are spinning between recruitment, selection and employee onboarding.

> "*If you considered chatbot for HR. It will help you in doing your onboarding, doing your recruitment, and also your employee engagement*." [Interviewee 5]

> "*I've been recommending chatbots for the screening process, scheduling interviews, and onboarding. Furthermore, it could also be used for engagement and talent acquisition*". [Interviewee 3]

Interviewees have agreed about the effectiveness of chatbots in recruitment and selection. As they have the ability to nominate candidates much faster and more efficiently than humans, taking into account the qualifications, competencies and skills of each individual which may assist in maintaining the organization's strategic objectives.

> "*Chatbots can help in recruitment and selection through calling out data from social platforms like LinkedIn and Facebook to give insightful information about candidates*". [Interviewees 1,2,3,4,5]

Among the most common features of chatbots identified from the perspective of the HR professionals, it could be highlighted their usefulness in employees' development:

> "*They are very useful in assessing and understanding at individual level. Furthermore, they are able to identify gaps in employees' profiles and then to look for educational references for each individual*". [Interviewee 4]

> "*Chatbot could use learning management system (LMS), in order to track and analyse the knowledge progress of individuals*". [Interviewee 2]

> Moreover, "*Chatbots can offer quick answers for the employees such as, how to apply for short leave or what is their leave balance or answering any other frequent inquiries to HR help desk*". [Interviewees 1,3]

In addition, chatbots "*can completely digitalize not only onboarding process, but also exit interviews or resignation. To illustrate, a chatbot could interview a resigned employee to* *identify the factors behind the resignation. It could use this information to further improve employee satisfaction in the company*". [Interviewee 5]

Regarding features from the candidate's perspective, they all agreed that chatbots meaningfully improve candidates' experiences and give them much more personal and humane attention and support.

"*Through help at the application stage and application status from a candidate perspective*". [Interviewee 1]

In other words, "*by using chatbots; candidates applying to the firm would feel as, they were the only one applying to this position in that firm and they were getting positive and interactive communication with the potential employer*" [Interviewee 3]. To illustrate, chatbots are able to "receive resumes and quickly skim it, screen it, see whether it is relevant or not, and in the case that it wouldn't be good enough, they are able to write back to candidates and explain them the status of their applications" [Interviewee 2]. Even more, some chatbots can guide candidates to the most suitable vacant position, for instance, "*if you land on a website, a popup will come and the chatbot would ask you: how could I help you? And then, different options for vacant positions in the company would appear. Chatbots could whether guide the candidate through the website offering vacant positions matching their qualifications, or in the case that the candidates were not satisfied, the chatbots will direct him to contact center*" [Interviewee 4]. "*Chatbots could ask some basic questions so that candidates would apply to a relevant job and even used across functional ability, they could also link candidates with more than one company having a similar vacant position*" [Interviewee 1].

Recruitment activities powered by Chatbots

The quality and accuracy of data is a significant issue for our Indian HR experts. The majority of interviewees believed that data generated from chatbots is positively influencing recruitment activities. In fact, chatbots are "interactive search engines with very customize functions".

"*They are able to reach out the targeted candidates by going into the internet and find out these active candidates*". [Interviewees 5]

"*Suppose the job has been raised in your company's website. The moment a job seeker will apply to that particular job post, the chatbot will open a window and it will start asking: What is your total experience? What is your location? What kind of salary are you expecting, and what are your skills?. The chatbot will automatically decide whether the candidate fits with the vacant position or not. If yes, it will automatically route the candidate to the interview centre*". [Interviewee 3]

Chatbots considerably simplify the job of the recruiter. The process followed by chatbots start with "*the understanding of what is written on the job description"* [Interviewee 2]*. Then, "they may start reading resumes and confirming whether the candidate might be suitable for the* *vacant position or not*" [Interviewee 1]. And finally, "*they could rate CVs based on the skills required and showed by the candidate*" [Interviewee 4]. The result and data generated from chatbots are more accurate and faster than in-charge employees.

"*Recruiter can set a particular alarm that goes off with any CV covering 70% of the job description; this CV would pass to the screening stage. Then chatbots could start with their work, as it could be: Hi, we're looking at four to six years of experience. Are you 4 to 6 years' experience in […]? Yes, OK, have you worked on [….]? Yes, have you worked on […] as have you worked on [….]? Yes".* [Interviewee 5]

"Then chatbots can do the screening. So chatbots could nominate 10 to15 people out of 100 or 300 without human intervention. Then I will be engaged with 10 instead of 300". [Interviewee 3]

Another feature drawn from this study is related to the ability of chatbots to conduct sentimental analysis.

"*When a candidate is asked a question, a chatbot will respond. But if the candidate comes with something that is not relevant, a chatbot will provide the candidate with a new window helping the candidate to focus on what is looked for*". [Interviewees 1,2]

In this vein, most of our interviewees argue that "chatbots lower down the workload of HR in recruitment from 100% to 50%" [Interviewees 2,3,4]. Furthermore, increase the productivity of the HR department allowing them to run deeper and more strategic tasks.

Advantages of chatbots in recruitment from the Indian perspective

According to the results of this study, companies adopting chatbots in recruitment could acquire three main advantages. Firstly, saving time/cost whilst minimizing wasting efforts. Particularly, these two pillars have a vital role in expanding the strategic functions of recruiters.

"*If you are able to save the time of a recruiter; the saved time will be used more effectively and strategically to other activities that could support strategical functions of HRM*". [Interviewee 4]

This argument is based on the ability of chatbots in sourcing and screening.

"*So, once the profile has been sourced from different channels, a chatbot could help in initial screening". "This is the power that we're talking about, sourcing and screening of {…} number of applications within seconds or minutes*". [Interviewee 1]

Along similar lines, interviewees also reported that chatbot plays a role in conserving time and effort by digitalising the entire onboarding through "*verifying individual background, introducing company's handbook and explaining the channels of communications within the company without human intervention*" [Interviewee 1]. Therefore, chatbots are very helpful also in personalizing onboarding with certain flexibilities on time, location, etc., based on the employee's desire. Therefore, the saved time from mentioned activities could expand the recruiter's role in supporting HRM in strategy-oriented functions.

Another advantage pointed out by interviewees was related to the fact that chatbot has a vital role in minimizing or ideally eliminating bias within the recruitment process. Discrimination against gender, colour and ethnicity in the recruitment process has been subject to debate in recruitment ethics (Yarger et al., 2020). Adopting chatbots in recruitment could eliminate these concerns by automatically sorting candidates according to the job description.

> "*Chatbots are new technologies around machine learning and artificial intelligence that prevent biases in the job description which should lead to avoiding biases in screening and selecting*". [Interviewee 3]

The third advantage referred to the influence of chatbots on candidate's satisfaction. Chatbots can assist recruiters by answering applicant's questions, such as application status or basic inquiries about the business culture, practices and career responsibilities. This fact not only saves a tremendous amount of time but also leads to a positive candidate experience.

> "*The role of chatbot could increase candidate's satisfaction by around 20% to 30% which could be reflected on company's reputation*". [Interviewee 2]

> "*It's a completely experienced product from the organization point of view; it really impacts your brand and reputation in candidates minds as well*". [Interviewee 5]

Moreover, interviewees also brought to light the advanced role of chatbots in replacing recruiters at the early stage of the interview. Chatbots in the first stage of the interview could analyze and study the logic and body language of candidates by asking general questions. This feature enhances the flexibility and minimize time restrictions of recruiters.

> "*Once a profile gets screened or shortlisted, the auto interview can also be aligned using chatbots. In that case, an auto mailer will go to stakeholders (stating that, this is the profile we are looking for, and we are looking for availability of yours to schedule an interview). Once the interview gets scheduled, a chatbot can help you with multiple levels of follow-ups*". [Interviewee 1]

> "*Suppose tomorrow at 3:00 o'clock your interview is aligned, and something happens, and your manager is not available. So, a candidate with a certain set of questions could still be interviewed by a chatbot. That interview would be recorded and it would be shared to the stakeholder's mail ID. So, after two days, three days or a week, depending on the manager's availability, he/she could review that interview and give his/her remarks. So, candidates did not wait for managers availability*". [Interviewee 4]

Chatbot limitation in recruitment activities

Despite the potential advantages of chatbots in recruiting, all interviewees have expressed concerns about the limitations of this technology. These barriers (listed in Table 2) may minimize chatbots' willingness to achieve the desired goals or exploit all their potential.

Table 2: Chatbots limitation in recruitment

No	List of main limitations
1	Chatbots are more effective in recruiting low managerial level employees.
2	Chatbots are unable to handle intangible skills of candidates.
3	Chatbots are unable to handle a qualitative conversation.
4	Disclose sensitive organization's data to candidates due to weak NLP.
5	Mistakes in extracting and understanding all information in CV's.

One of the biggest concerns agreed by interviewees, are related to the scope and the ground of chatbots in recruiting. Chatbots could interact with all vacant positions within the organization, no matter the position, from managers to receptionists. However, chatbots are facing challenges in analysing data extracted from candidates for senior positions. Based on the fact that, managerial positions are depending on tangible and intangible skills.

> "*I believed that chatbot applications could really work a lot better for maybe middle to bottom of the pyramid of the organization. But when it comes to the upper half of the pyramid, it would continue to be a lot more human-driven. Because there are more about network or leadership*". [Interviewees 1,3]

> "*Recruiting for high senior positions, assessed based on the leadership and managerial (intangible) skills of candidates; this is difficult to implement by chatbots*". [Interviewee 4]

> "*Chatbot can only replace the transactional query. It can't really have a qualitative conversation. Especially hiring chatbot is not helpful if you are talking about a mid-level and senior-level*". [Interviewees 1,2,4]

Another concern is related to interpreting data. For example, chatbots have difficulties in extracting and understanding all information in CV's correctly, which reflects on candidate assessment.

> "*There could be a situation that it may roll out extremely good candidates because the CV is not made in the way that chatbot is able to read it. Or it can also shortlist terrible candidates*". [Interviewee 2]

These incidents are related to, on the one hand, the weak algorithm of natural language processing (NLP) in chatbots, which may disrupt communication between users; as interviewees reported:

> "*Chatbot couldn't be developed without NLP algorithm, because it's a key for successful communication*". [Interviewee 3]

On the other hand, fuzzy words and grammatical mistakes may confuse chatbots to interpret candidate's inquiries correctly (Schildknecht et al., 2018).

On these grounds, the authors raised a question: If chatbots could replace all recruitment activities? All interviewees had shared the same opinion that chatbots need a large amount of data and still far away from replacing all employee's activities. Limited training data results in poor performance, which may further discourage the use of chatbots as a recruiter. Below are some citations for interviews respondents:

> "*Chatbot replaces recruiter, definitely no. There are elements that only human can do them. For instance, understanding the person's ability under pressure; analyzing the teamwork skills of a group of candidates; understanding the cultural background of the candidates. So Chatbots cannot do that*". [Interviewee 3]

> "*No, I don't see that possibility at all, because chatbots are still unable to analysis IQ and soft skills*". [Interviewee 2]

Overall, we are still in the stage of chatbots-recruiter correlation because "*the technology hasn't really evolved to that level where you would be able to mimic completely what recruiter do or think*". [Interviewee 1]

AI-powered chatbots in India

All interviewees had declared the need for more mature chatbots in recruitment as the fact that no chatbots perform all recruitment processes in the Indian market.

> "C*hatbots for full recruitment activities are not available as of known in India*". [Interviewee 4]

> "*Pure Indian chatbots for recruiting are not available, however some global companies developed their own chatbots such as Mya, Olivia, Jobpal. These are examples of advanced chatbots that built based on NLP and machine learning*". [Interviewee 1]

This claim from our interviewees forced authors to analyize the Indian commercial brands of chatbots in HR. The motivator for this investigation is Stanford University's claim that India is ranked as the top developed AI country according to the Global Vibrancy Ranking 2020 (Saxena, 2021).

Investigation reveals that, many IT Indian companies developed several HR Chatbots to facilitate the functions of the HR department in several areas and not limited to recruitment (Mohan, 2019). See table 3

Table 3: Indian developer for HR Chatbots

No	Company Name	Chatbots Name	Chatbots functions
1	People Strong	Jinie	Employees receive personal work aid and support with job-related issues such as applying for leaves and addressing corporate policy inquiries.
2	Phenom	Phenom Chatbot	Allows individuals to search for opportunities, ask questions about registered firms, and obtain customized job suggestions
3	Param.ai	Parami AI	Automate candidate screening, shorten the time it takes to fill jobs, and provide a better candidate journey
4	Mettl	Mettl Dark Personality Inventory	Skill assessment tools, proctoring, and online assessment software
5	Talview	Talview Behavioral Insights	End-to-end, AI-powered hiring and proctoring solution
6	Tech Mahindra	UVO chatbots	AI-powered technology that aids in the selection of the best candidate based on the job description

Based on the above details, Indian HR consultants are not following the latest development of local AI-powered chatbots in recruitment. As a result, the competitive advantages of Indian companies may be affected by losing opportunities in attracting high skilled candidates.

Chatbot's future in recruitment activities

It becomes obvious from our interviews that although chatbots in recruitment were perceived as a source of debate, it was challenging for the HR experts in our Indian case companies to ignore the bright future of chatbots in recruitment; as one interviewee said:

> "*To be very honest, the future is already very bright for these chatbots. Chatbots always come as a supporting hand to us. If I work alone, I will be productive but with the help of a chatbot I will be double productive at the end of the day*". [Interviewees 1,3,4]

Most of our interviewees admitted that HR professionals should rethink about the interaction style of chatbots. In other words, voicebot will probably replace text conversation dialogue.

> *"We are currently don't know exactly what is the future of the chatbots. In my personal opinion, chatbot will not remain as a chatbot but may move to a voicebot. Is something that I see from a longer perspective".* [Interviewees 2, 5]

> "*I am assuming that, these voices assistants and chatbots will come with fewer restrictions, high productivity and they will be able to get a bigger portion of the recruiter in the nearest future*" [Interviewee 3]

According to our interviewees, the future of chatbots depends on the development of two factors. Firstly, the development in data analysis and NLP. This factor is in parallel with Rahman et al. (2017) argument, that getting NLP is one aspect of designing and developing chatbots while Machine Learning is another aspect of chatbot design and development.

> "*Chatbots coupled with the development data analytics and NLP in solving the problems of recruiters in terms of time and sourcing*". [Interviewee 1]

Secondly, the ability of chatbots in dealing with unstructured conversation;

> "*The future of chatbots is linked to the ability to drive information from unstructured conversation*". [Interviewees 3,4]

> "The future of chatbot is linked with the *moment you ask a question not related to previous one, even in the different format; but in the end, you get answers for diverse questions,*". [Interviewee 2]

Based on that, interviewees tried to predict some future functions for chatbot/voicebot in recruitment. For instance:

> "*Incoming years there will be plenty of voice assistants, avatar, who will do onboarding in a couple of hours. We are actually looking forward to those multitasker chatbots in future*". [Interviewees 1,5]

> "*Future chatbots should integrate cognitive computing with multitasking problem solving in order to balance between job search versus job recommendation*". [Interviewees 2,4]

> "*In the future, chatbot comes up and says: We just had one candidate who just logged into the system, and he is being recommended by our job search algorithm; he got 70% out of it. I have done an assessment and he or she fits the requirements. So, the recruiter could spend additional time talking to this candidate and give him the offer at the end of the day*". [Interviewees 3,4,5]

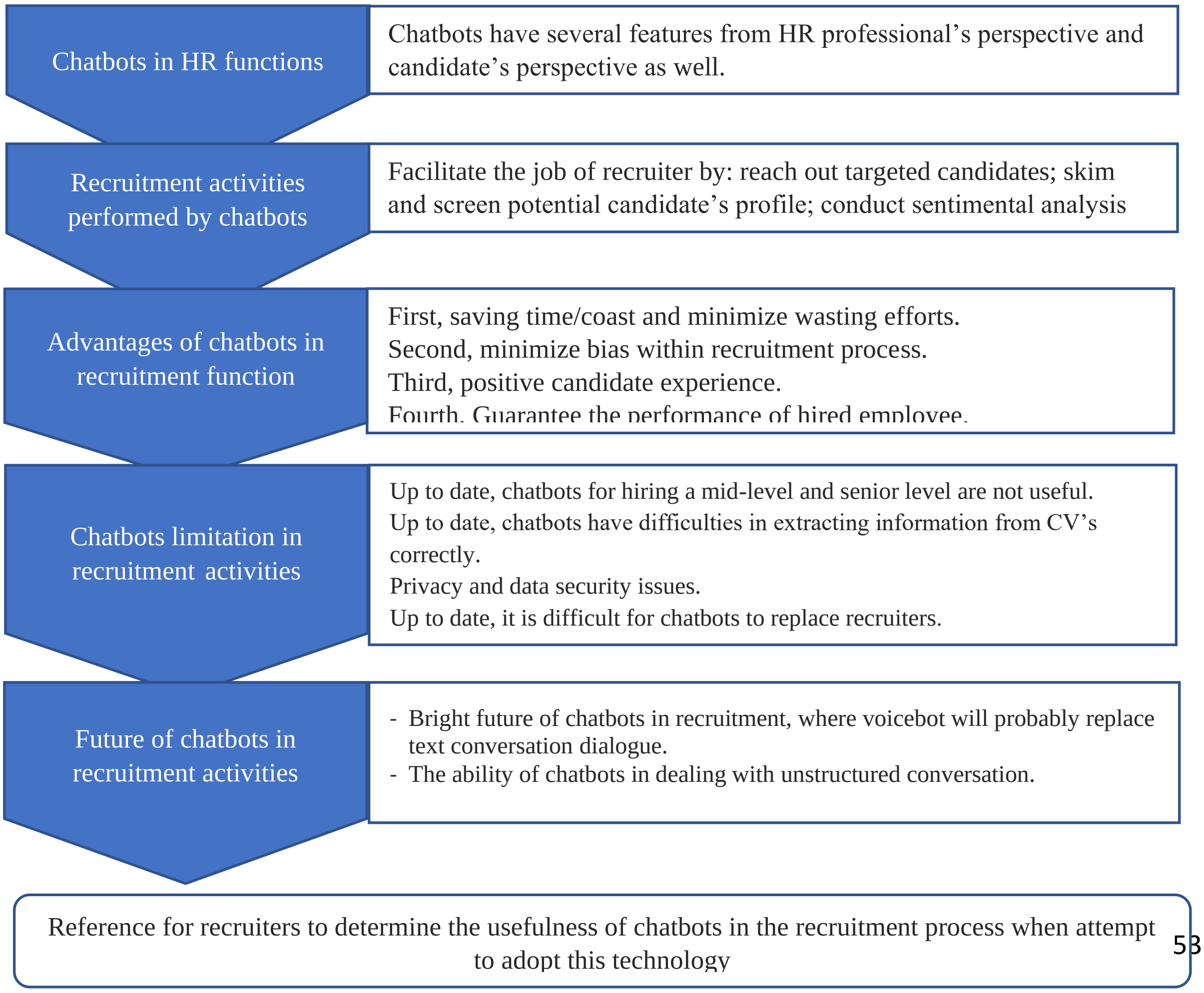
This technology has been successful in simplifying the work of HR professionals and also in collecting information related to candidates. But, still not clear the future of chatbots especially regarding the involvement level and the scope of their implementation in recruitment.

Conclusion

This piece of research has been designed to explore the usefulness and limitations of chatbots in the recruitment process in India, at the same time the reflection on hired employees' performance. This topic has been selected since it potentially represents a novel paradigm in how recruiters may interact and understand chatbots in the future. It has been shown that, although the first investigation about AI-powered chatbots has emerged in the last few years, there is a clear lack of empirical investigations into the use of AI-Powered chatbots from an HR professional's perspective, specifically in the Indian market (Srivastava, 2018). The findings of this study show several insights and practical implications. One of the main conclusions drawn from the study is the need for mature chatbots in recruitment. Since the significant positive effects of recruitment on employee performance. This result is matching with Pahos and Galanaki (2019) argument that organizations are invited to invest in recruitment to maintain the performance and efficiency of employees. Furthermore, as it has been seen that, there is a gap between what are Indian IT companies offering for recruiters and what are recruiters know about the latest development of the chatbots in the Indian market.

In terms of practical applications, based on the results of this study, the current approach of chatbots in recruitment in India could be mapped as shown in Figure 1. These contributions could enhance the awareness of CEOs and stakeholders in terms of adopting chatbots in recruiting.

Figure 1: current approach of chatbots in recruitment from Indian HR perspective



The present study is subject to limitations. Due to the novelty of the research, a qualitative study has been performed and the sample of interviewees is relativity small compared to a huge market like India. Therefore, conducting a quantitative study with a larger sample could be an interesting challenge for future investigations. Especially, when scholars differentiate between the role of chatbots in recruitment based on different business areas like logistics or marketing.

Moreover, this study doesn't consider several geographical regions and languages in India; it is essential to note that there are 255 official languages all over India (Javaid, 2021). Therefore, replicating the study in specific regions or languages, instead of English, may lead to different results.

Due to the fact that chatbots in recruitment are still an emerging technology, identifying the transforming role of AI-powered chatbots on the part of HRM functions such as: staffing, training and development and motivation; would be another possible line for future research.

4.3 Article 3: "Key elements in transferring knowledge of the AI implementation process for HRM in COVID-19 times: AI consultants' perspective"

Title:	Key elements in transferring knowledge of the AI implementation process for HRM in COVID-19 times: AI consultants' perspective
DOI:	---------
Format:	Journal Article
Journal:	International Journal of Business Science and Applied Management
Language:	English
Journal Metrics	Scopus, Q3 . Cite Score: 1.1
Status:	Accepted Volume 17, Issue 1, 2022
Keywords	Artificial intelligence, implementation, HR Manager, employee, Covid-19

Abstract

Although artificial intelligence (AI) is transforming the workplace structure, very little is known about the strategy that facilitates AI implementation into organizations. The purpose of this paper is to explore key elements in transferring knowledge of the AI implementation process in human resource management (HRM) from the perspective of AI consultants. This study utilizes qualitative data analysis techniques. We first review the literature and then conduct in-depth semistructured interviews with eight AI consultants. We analyze transcripts using the ATLAS.ti software. First, this research reveals that AI implementation is affected by shortage of employee data, no clear vision, a limited understanding of the AI decisions framework and managers' desire to bypass AI decisions. Second, the combination of an intensive training program and assigning AI specialists is the best way to transfer the knowledge of AI implementation processes to HR managers. Third, HR managers should create communication channels and enhance employees' awareness of the positive impact that AI solutions have on smooth collaboration with AI-employees. The paper also reveals that accelerating the process of implementing AI applications has no negative impact on organization performance during COVID-19 times. However, an AI bias may be considered a potential threat for AI implementation. This paper attempts to provide a practical understanding of the elements that facilitating AI implementation in the HRM process. It provides vital insights for HR managers and AI developers to benchmark their activities when designing and adopting AI solutions. It also contributes to the literature by responding to the question of how AI implementation should be provided to HR managers and employees.

Introduction

Data are becoming the most valuable asset for any organization and might be its only truly inimitable asset (de Medeiros et al., 2020). Organizations have ample access to massive volumes of data from several sources, which, when reliably and quickly processed, significantly increase the likelihood of obtaining valuable insights to guide decision makers and employee performance in the HR department (Wan & Liu, 2021). HR data play a crucial role in guiding the performance measure in the competitive business environment. This includes employee data, such as employee performance, employee behavioral patterns, attendance, compensation and other personal data (Pillai & Sivathanu, 2021). Researchers have noticed that data strongly influences strategy formulation because the increase in data and analytical capabilities is redefining innovation, competition and productivity (Nisar, et al., 2021). According to an interview published by the McKinsey Global Institute, conducted by Barr Seitz and Rob Roy: “Having a data-first mentality is a crucial first step, but then you need to put in place the processes and capabilities to be able to use this data” (Seitz & Roy, 2018).

Therefore, HR data needs to be appropriately managed to maintain data quality depending on two assets: emerged technology and human asset (Yablonsky, 2021).

Artificial intelligence (AI) is considered the most advanced technology that transfers the nature of the workplace and relationships among employees. Based on a study conducted by McKinsey and Company in 2020 about the state of AI, revenue increased from adopting AI in human resources by 55% and adopting AI across several teams led to 33% increased team efficiency (McKinsey, 2020). These advantages of AI depend on a large set of technologies that allow the computer to perform many HR tasks that generally require human intervention. These tasks extend to covering data mining in recruitment and selection (Allal-Chérif et al., 2021), employee turnover (Zhang et al., 2021) and data extraction, with an emphasis placed on employee performance and productivity (Arslan et al.,2021). For instance, IBM and Microsoft are using AI and data mining to identify suitable candidates for particular jobs by, therefore, standardizing candidate sourcing and C.V screening methods for all their subsidiaries (Garg et al., 2021). Similarly, Human Capital Management (HCM) from Oracle is using data-driven insights, which help with talent acquisition and advanced HR metrics as a part of AI–HR process integration (Fernandez J. , 2019).

HR data-driven solutions have a constructive effect on survival during times of crisis and pandemics (Vahdat, 2021). COVID-19 is a contagious infectious pandemic that negatively influences major economic sectors globally. This influence is driven by a series of widespread lockdowns of various sizes, marking it as the first crisis and life-changing phenomenon of its type for nearly 7 billion people around the world (Nguyen et al., 2021; Nizamidou & Vouzas, 2018). This crisis has, in turn, posed financial challenges for organizations as a result of a massive decrease in product demand and sharp declines of in-house employees' numbers due to isolation and social distance, which inevitably lead to fewer investments (Adikaram et al., 2021). On the one hand, companies are concerned to ensure their employees' health and safety. On the other hand, curtailing the spread of this virus means having to make drastic changes in the workplace structure and employee performance (He et al., 2021).

Disruption in the actual workplace, such as that caused by COVID-19, prompts the need for a novel solution to facilitate remote working options. The AI-powered solution is bridging the physical world and the digital world by strengthening human-machine interactions and fostering automation through integrations between smart machines and HR tasks (Pereira et al., 2021). Accordingly, AI is considered the recent key answer for unexpected situations faced by individuals and corporates related to business survival in disasters (Kashyap & Raghuvanshi, 2020). In fact 52% of US companies are accelerating their AI investments in the wake of the COVID-19 crisis in different company areas (PwC, 2020). One international bank has created a source of truth from datasets and launched an AI-powered chatbot to respond to customer queries. These efforts not only helped customers, but also demonstrated to employees the role of AI in facilitating job demands (McKinsey, 2020). Therefore, AI implementation acts as the optimum solution for organizations and technology developers to bypass COVID-19 challenges.

On the other side of the story, human asset, HR managers and employees are playing a crucial role in maintaining the quality of data and enrolling these data in AI-powered solutions to leverage these solutions (Wiblen & Marler, 2019). Both HR managers and employees have witnessed the advanced role of AI applications in several human resource management (HRM) functions. From a manager's perspective, AI facilitates the functions of collecting, managing, analyzing and visualizing large amounts of data to generate recommendations and insights (de Medeiros et al., 2020). From an employee's perspective, AI enables employees to work in both physical and virtual spaces. These facilities will help employees to save useless commuting time, provide them with more flexibility, enable them to manage work and collaborate with no time and place constraints (Malik et al., 2021).

Organizations have taken the advantage of AI in different ways, which has led to a massive change in the landscape of HR processes. However, there are still challenges and difficulties to be addressed with AI advantages (Tambe et al., 2019). For instance: data generation stage, employees' learning capabilities, the accountability questions associated with fairness and ethical constraints, possible adverse employee reactions to management's decisions via data-based AI (Harney & Collings, 2021). These challenges have brought about the need to enhance HR managers' knowledge about AI and how this technology should be adopted among their employees. Kolbjørnsrud et al. (2017) report that managers are not confident enough about AI. Their readiness and enthusiasm for AI may vary extensively across organizational levels, which raises serious questions about the optimum strategy for sharing knowledge of the AI implementation process.

The importance of extending HR managers and employees' knowledge about AI implementation has been further highlighted by Chang (2020). He calls for further studies to investigate the best HR managers-employees balance for AI implementation and how knowledge of AI implementation processes can be provided to HR managers and employees. At the same time, the current massive challenges posed by COVID-19 provide an opportunity for management scholars to extend research efforts and turn them into actionable insights. These initiatives will support organizations in handling one of the greatest challenges in modern history by identifying the potential impact of COVID-19 on AI implementation (Hamouche, 2021).

Despite several studies having been conducted on AI implementation in HR tasks, such as recruiting, selecting and performance management (Wall & Schellmann, 2021; Tuffaha & Perello-Marin, 2021; Xiong & Xia, 2020), there is still a gap in the literature in terms of understand the best HR managers-employees balance for AI implementation. To overcome these gaps, the following research questions (RQs) are raised:

RQ1: How can the knowledge of the AI implementation process be transferred to HR managers?

RQ2: What kind of strategies can HR managers adopt for smooth AI implementation among employees?

Our analysis contributes to the literature about HRM in AI in several ways. First, we develop a practical understanding for the elements facilitating AI implementation in the HR department during a pandemic. Second, our study responds to Chang's (2020) request to research the best-demand equilibrium for AI implementation. Finally, this novel research will be beneficial for HR managers and AI developers when designing and adopting AI solutions.

The article is organized as follows. We first provide a literature review. Then we discuss the methods. Next we analyze the categories reported by the participants. This is followed by a section with discussion and implications. The final section offers some conclusions.

Literature review

This section attempts to look closely at what is currently known about AI solutions in HR, the role of AI in the COVID-19 times and the effects of AI implementation on HR managers and employees. We review the literature and technical reports on AI and HRM. Furthermore, HRM and COVID-19 are considered.

Impact of technologies on HRM

For several decades, scholars have been studying the impact of information technology (IT) on HRM. One of the main study areas is E-HRM: the planning and implementing of IT among employees for collective actors of HR activities (Poba-Nzaou et al., 2020). Subsequently, scholars have focused on big data and the development of HR analytics in organizations (Dahlbom et al., 2020). Later scholars have centered on the implementation of AI, data mining, HRM cloud computing and algorithms in functioning HR tasks (Alrashedi & Abbod, 2021; Black & van Esch, 2021; Marin et al., 2021), and access to and the creation of structured and unstructured HR-specific datasets with growing dependence on advanced digitalized HRM and AI applications to generate insights, solve issues and participate in HR decision making (Caruso, 2018; Prikshat et al., 2021; Vrontis et al., 2021). The diffusion and applications of AI-innovated database management are demonstrated by emergent AI-HR solutions, such as SAP SuccessFactors, ERP and CloudHR (Oracle, 2022; SAP, 2022). Google, Microsoft, IBM and LinkedIn are among the IT behemoths that have also created such applications. The job of HR professionals involves redefining and restructuring as a result of greater digitization and data utilization by AI-powered HR solutions (Qamar et al., 2021).

AI is defined as a smart machine-based system's ability to correctly interpret data, find patterns and adopt the resulting information to fulfill specific goals and to perform tasks (Arslan et al.,2021). AI uses several techniques, such as the Internet of Things (IoT), deep learning, pattern recognition, machine learning and artificial neural networks (ANN) (Ali & Frimpong, 2020). The main advantages of AI, such as high-speed processing, big data mining and sophisticated prediction and analysis, differentiate AI from existing heritage IT applications (Cheng & Hackett, 2021). These advantages help HR managers to save time and to make accurate decisions (Borges et al., 2021) in critical tasks like recruitment and selection, performance management and workforce planning (Black & van Esch, 2021; Santana & Valle-Cabrera, 2021).

AI in HR amid COVID-19

The COVID-19 pandemic has created uncertainty in not only firm productivity and operation terms, but also in HRM efficiency terms. Therefore, significantly increased attention has been paid to AI during COVID-19. This demand is related to several novel applications with have abilities to facilitate virtual workplaces. Organizations have leveraged AI in HRM during COVID-19 from several dimensions. For instance, first AI-powered chatbots have facilitated the role of the HR department in conducting virtual recruiting and to arrange interviews without candidates having to physically travel to the workplace (Sowa et al., 2021). Second, AI plays an advanced role in training and development by analyzing the data collected from employees and test results, and then building individual development programs based on these results (Boiral et al., 2021). Third, AI also plays a role in monitoring and analyzing employees' culture enrollment and engagement by identifying behavioral patterns (Rao & Krishan, 2021). To illustrate all this, AI-enabled automation tools can handle and analyze massive volumes of data, recommend courses of actions and carry out these recommendations (Vahdat, 2021). As a reflection, HR managers can virtually operate HR departments.

AI applications in HR tasks during COVID-19 have raised employees' concerns about their existence (Mohamadou et al., 2020). Many scholars argue that fully adopting AI applications will reduce aggregate labor hours (Frey & Osborne, 2017), which will imply fewer employees, while others claim that many AI applications are useless without employees intervening (Dwivedi, et al., 2021). Employees are required to analyze and confirm AI recommendations, convert recommendations into courses of actions and offer backup if an AI solution fails. As a result, a new trend of an AI implementation scenario is formulated that depends on boosting employee productivity by AI-enabled technology rather than replacing them (Dwivedi, et al., 2021).

The opportunities for AI are numerous. To accomplish the potential leverage of these applications, organization should maximize "AI-human integration". This integration should be based on detailed information about the AI implementation process (Wilson & Daugherty, 2018). Therefore, this paper attempts to bridge the following gap: in what circumstances and to what extent can organizations transfer knowledge about AI implementation processes to HR managers and employees? It also studies the impact of COVID-19 on AI implementation.

Research Methodology

Data collection

The study took a qualitative approach to examine the data collected from eight AI consultants experienced in implementing AI into HR projects in multi-international firms. These professionals were identified using LinkedIn (see Table 1) to obtain a more holistic overview of the research questions. LinkedIn has had major implications for recruiters, hiring managers and job seekers. It is used by over 40% of potential job seekers and 85% of hiring managers for the purposes of screening applicants and other recruitment processes (Collmus et al., 2016; Cubrich et al., 2021).

Table 1. Interviewees' profiles for the third article

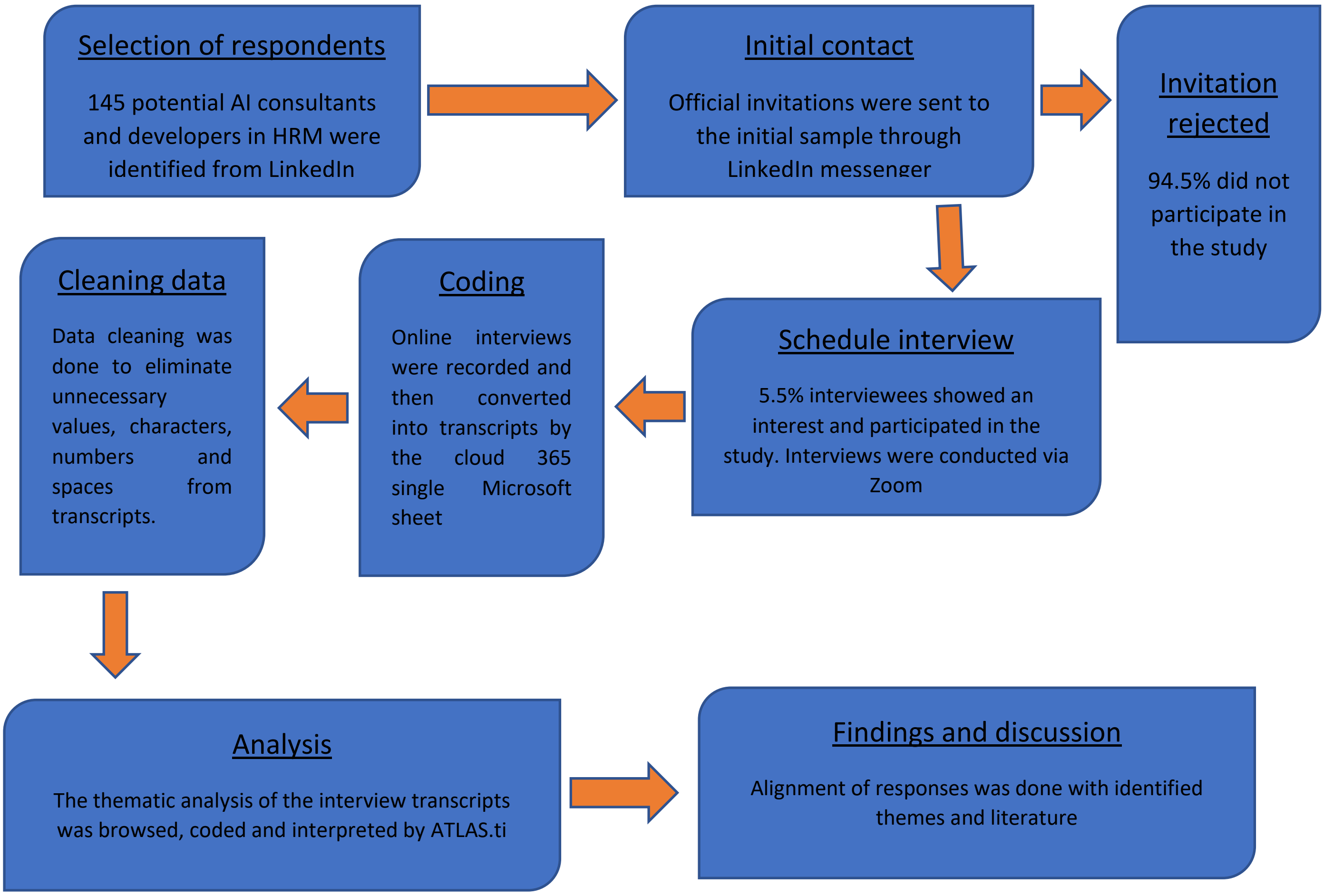
Num.	Title / Position	Years of experience	Area of experience	Company Size	Interview style
1	Senior Artificial Intelligence and SAP Consultant	over 16 years	Technology leader with expertise in NLP, Deep Learning, Analytics and SAP.	More than 1000 employees	Online interview (via Zoom)
2	Co-founder of impress.ai	over 14 years	AI-Powered Chatbot Platform for Recruiters	84 employees	Online interview (via Zoom)
3	Senior Artificial Intelligence (AI) Developer at Cloud Solutions	13 years of experience	Specialist in : - AI in healthcare - Business Analyst - Full-stack Development (Web & Mobile)	More than 500 employees	Online interview (via Zoom)
4	HR & Talent Tech Start-up Advisor, AI Educator and Organizational Consultant	15 years experience	- Businesses Adviser for AI and emergent technology in HRM functions		Online interview (via Zoom)
5	SAP Success Factors Consultant	11 years	- SF/SAP solution consultant, business process analyst, team leader, integration consultant, trainer, onsite service coordinator and career counselor. - Senior system engineer at IBM	Around 200 employees	Online interview (via Zoom)
6	Director Solutions Consulting (Gulf region) HCM at Oracle	over 16 years	- AI in HRM implementation consultant - Solution orientates for HRM project	110 employees	Online interview (via Zoom)
7	Hiring Solutions Selling Professionals (Cloud, CyberSec, & AI)	10 years of experience	- Cybersecurity & compliance - Software Engineering (Custom Applications Development - Enterprise) - Cloud & Infrastructure - Data Science and Advanced analytics	400 employees	Online interview (via Zoom)
8	Director, AI & FinTech Leader in PwC	over 16 years of experience	- Helping PwC and its clients benefit from global AI insights and expertise - Leading the development of AI-enabled products and solutions		Online interview (via Zoom)

As the table shows, interviewees' average work experience is 13.87 years. During the interviews, we asked questions about how the AI implementation process can be provided to HR managers and employees, and then about the impact of COVID-19 on AI implementation.

Data analysis

To evaluate the collected data, we used the following procedure (see Figure 1). In the first step, interviews were coded into text and turned into a transcript by compiling replies on a single response sheet for each research question individually. In the next step, the transcript was cleaned of special characters, numerical values and spaces. Finally, these transcripts were imported to the ATLAS.ti qualitative data analysis software (Paulus & Lester, 2016). The team working on establishing reliability and validity consisted of two researchers; each one has prior research experience and works as an Associate Professor in a management college. A word cloud was created, which was then utilized to extract the major content from the analysis. A mixture of text mining and qualitative content analysis (Using ATLAS.ti) was applied so that thematic convergence was evident from the data collected from the interview transcripts.

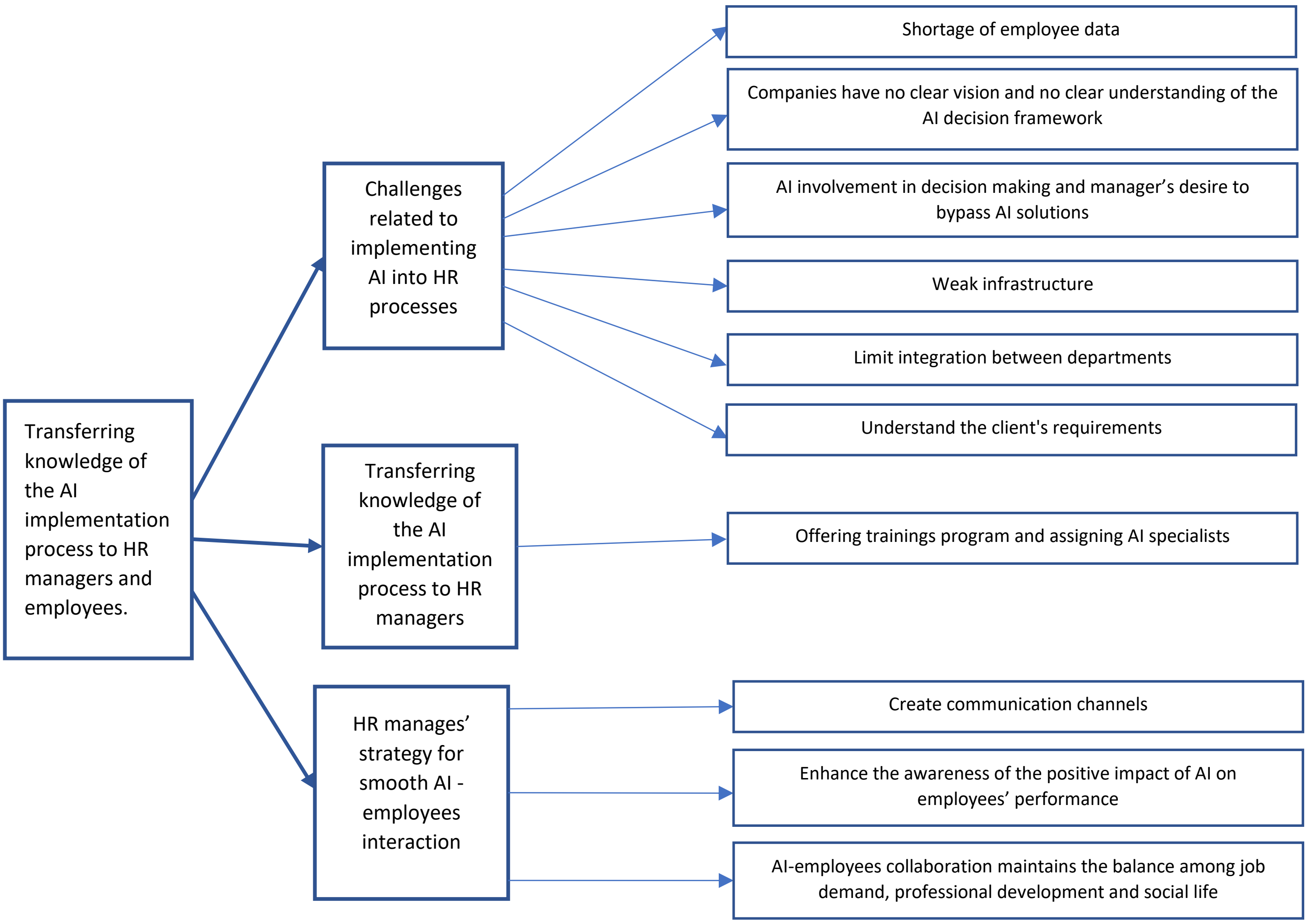
Figure 1. Data collection and analysis process (Third article)



Findings

The analysis of interviewees' responses revealed three major categories: 1) challenges associated with AI implementation in the HR process in COVID-19 times; 2) transfer of knowledge about AI implementation processes to HR managers; 3) HR manager's strategy for smooth AI-employees interacting (Figure 2). The first two categories addressed the first question, while the third category dealt with the second question.

Figure 2, Key elements to transfer knowledge about AI implementation processes for HRM in COVID-19 times.



<u>Challenges associated with AI implementation in HR processes in COVID-19 times</u>

The word cloud for the first research question indicates that "AI Data" is the word that was highlighted the most by the interviewees, followed by vision, clear, accept, solution, bypass, infrastructure, etc. The thematic analysis of the first research question indicated some barriers and challenges for implementing AI into the HR process (see Table 2). Interviewees highlighted weak employee dataset, which minimized the efficiency of AI functions. Data and

AI are merging into a synergistic relation, where AI is useless without HR data sources like personnel employee data, employee performance and financial data. In contrast, mastering these data is difficult without AI solutions. This idea comes over in the following remarks:

> Interviewee 5: "*Of the key challenges for AI we find data availability in organizations. If it's available, it might not be central enough*".
>
> Interviewee 2: "*Data collecting and processing speed have enabled the development of AI. This development leads to analyze data which help to assess and predict employee performance*".
>
> Interviewee 7: "*Massive volumes of data would be worthless unless AI models unlock the potential of these data and turn them into information*".

Table 2. Themes identified for Research Question 1 (RQ1) (Part 1) (Third article)

S. No	Themes	Frequency	Percentage
1.1	Employee data and data quality	10	20.5
1.2	Companies have no clear vision or a clear understanding of the AI decision framework	9	16.66
1.3	Managers' desire to bypass AI decisions	8	11.2
1.4	Weak infrastructure	7	7.6
1.5	Limit integration between departments	3	5.1
1.6	Understand the client's requirements	2	4.5

Note: Only themes having a frequency of more than two were included

The next theme was the unclear vision on the areas where AI is used to support organizational performance (16.6%), which resulted from the ambiguity as to how AI is building its decisions or prediction. HR managers frequently lack an understanding of the assumptions and decisions made by AI. They also need standardized assessments of the overall risk and financial metrics of AI like return on investment (ROI). Additionally, tools that explain how AI systems make decisions could enable managers to better understand the potential risk associated with AI implementation. Quoted below are some instances from interviewees' answers:

> Interviewee 3: "*One organization's manager told me: we are facing problems to build a clear vision for the future of AI in our company resulting from the ambiguous process of AI*".
>
> Interviewee 4: "*HR managers need a clear conceptual model to analyze the ROI when adopting AI in their departments; such as potential risks and financial impacts. We know the features of AI, but managers are unaware of the disadvantages of AI in their departments*".

Another theme is that managers wish to have the authority to bypass AI solutions (11.2%). AI has wide applications for integrating information, analyzing data and using gained insights to improve employee performance. However, interviewees admitted that their organization's manager wishes to have the upper hand in the final AI decision related to employees. Some instances from interviewees' answers are quoted below:

> Interviewee 6: “*Another challenge that we are facing is: to what extent should AI be involved in decision making? Some HR managers would like to use AI internally but, at the same time, they want the authority to bypass AI solutions*”.

> Interviewee 3: *“Some companies are not responding to AI recommendations, which poses obstacles to machine toward generating correct decisions in the future”.*

Finally, another aspect worth highlighting is that all interviewees shared the same impression: AI is the best solution that organizations should adopt to manage their employees and to minimize the influence of uncertainty and confusion. Therefore, AI-powered solutions and implementation are in great demand in COVID-19 times. These responses are reasonable if we analyze the advantages of AI in the virtual workplace. These advantages include but are not limited to: 1) the role of AI-powered solutions in effectively achieving employees' tasks; 2) helping the HR department to follow up the analysis of the sentiment of employees and to flag up employees' concerns; 3) detect employee engagement trends across specific employee segments (PwC, 2020)

Along similar lines, all the interviewees also reported that accelerating AI implementation during pandemics does not have a negative impact on organization performance. However, interviewees voice a concern about the negative impact of the AI bias on organizational performance.

An AI algorithm decision is based on training data, which may either include biased human decisions or reflect historic or social concerns, even if sensitive variables like gender, race or sexual orientation are removed. Algorithm biases reduce employees' ability to participate in developing their organization by encouraging mistrust, which may produce inadequate results.

Business and organizational leaders need to ensure that the adopted AI system is free from algorithm bias to maintain the quality of the decision-making process. They have the responsibility to encourage the progress of research and standards that reduce any bias in AI to eliminate potential negative impacts from implementing AI. The following remarks made by AI consultants reflect this approach:

> Interviewee 3: “*if we have an algorithm that is biased toward women because of training data, this will be reflected on the determinant of women's future success, and women who have trained will be subject to an AI algorithm bias because most leading positions have to be for men*”.

> Interviewee 6: “*The role of imbalanced data is vital for introducing bias. Feeding AI with the correct dataset is vital to maintain the perfect image in the face of our employees. Otherwise AI implementation will collapse*”.

Based on our data, it would appear that while AI is a tempting next step toward creating value for organizations and employees, shortage of data and the relationship of mistrust between AI and managers have been considered a barrier for AI implementation. These challenges are boosting the need for initiatives that eliminate the risk of users being threatened by AI implementation. This message is similar to a project launched by the European Union called “TRUST-AI” (European, 2020) to develop trust in AI adequacy to tackle predictable.

Key factors in transferring knowledge about the AI implementation process to HR managers

Another word cloud created for the first research question showed that “AI training” and “AI specialist” were the words highlighted by most interviewees, followed by knowledge, technical, consultant, person, function, etc. The thematic analysis revealed two main defined themes (see Table 3). According to interview data, interviewees took two different points of view about the best way to transfer knowledge of AI implementation processes to HR managers.

The most prominent ones were that transferring knowledge about AI implementation depends on two key factors: offering a training program for HR managers and assigning AI specialists (67%) to follow AI implementation progress.

Table 3. Responses for Research Question 1 (RQ1) (Part 2) (Third article)

S. No.	Themes	Frequency	Percentage
2.1	AI provided for HR managers by Internal training and AI consultant/specialist	32	67.3%
2.2	AI provided for HR managers by internal training only	14	22.2%

Note: Only the themes with a frequency of more than 2 were included

AI’s contribution to the organization’s performance depends, on the one hand, on enhancing HR managers’ knowledge by an intensive training program and, on the other hand, appointing an AI specialist in the organization. Quoted below are some instances from interviewees’ answers:

> Interviewee 1: *“If I need an AI solution for interviewing candidates, this kind of solution needs the recruiter to be familiar with the AI system. At the same time, AI technicians should be available in the organization to maintain data and to cover any problems if the system collapses.*”
>
> Interviewee 7: “*I believe that internal training is not enough alone. The organization should assign an AI specialist who is aware of this recently emerged technology to maintain the follow-up of data in the AI solution*”.

To maintain the quality of the first point of view (Theme 2.1), and to explore the potential negative impact on the organization’s performance, the authors followed interviewees’ answers with another question: “If AI specialists are hired, could the role of AI specialists overlap that of decision makers?”. The first point of view believed that AI specialists would have no reflection on HR decisions for two reasons: 1) AI specialists do not work for the HR department only, but facilitate AI implementation for other departments within the organization; 2) AI specialists work as consultants only because HR managers have the qualitative and quantitative skills, which are difficult for AI specialists to acquire. Some instances from interviewees' answers are quoted below:

> Interviewee 7: "*AI specialists should do cross-company work, and not just deal with HR. They are solutions-oriented and AI specialists perform cross-domain functions*".

> Interviewee 4: "*AI specialists provide and explain why this recommendation is proposed. They play no role in final management decisions*".

The second point of view (Theme 2.2) emphasizes that the training program is a sufficient way to transfer knowledge of the AI implementation process (22%). Here it was argued that personal data and employee performance data should remain confidential and not be exposed to any third party. Quoted below are some instances from interviewees' answers:

> Interviewee 2: "*We should not accept the AI specialists' point because [1] of data privacy, and [2] they could guide us in the wrong direction, which could affect on the functionality of the HR department*".

> Interviewee 4: "*Training is key for AI implementation. We can't expose our employee data to a third party. We can go for some kind of external support, but only at the beginning. But, in the end, you have to manage the whole process*".

The first point of view is in line with the finding reported by Khabiri et al. (2012). They claimed that the most important aspect of technology transformation is how to transfer technology and which mechanism offers the transferee more benefits. Collaboration between the transferor (AI specialist in our case) and transferee (HR managers in our case) is essential for the smooth implementation of new technology. Therefore, in parallel to what is mentioned above, the authors decided to follow the first point of view as a key factor for transferring knowledge about the AI implementation process to HR managers.

HR managers' strategy for smooth collaboration with AI-employees

A word cloud was generated for the second research question, which indicated that "communication" is the most frequent word used in the responses, followed by awareness, acceptance, collaborative, orientation, partners, integrate, help, future, efficiency, etc.

The thematic analysis for the second question revealed some definitive themes related to smooth AI implementation among employees (see Table 4). Themes were categorized as creating communication channels (19.4%). This implies that HR managers can gain insights into what things are threatening employees from implementing AI by expressing their ideas and perspectives without criticism. These HR managers-employees discussions and communications are the best way to build a strong relationship, remove ambiguous and increase the efficiency of AI-driven solutions. Aligning the AI-business goals with the capital strategy in a wide range of attitudes, behaviors and intentions could strongly impact smooth AI implementation among employees. Quoted below are some instances from interviewees' answers:

Interviewee 2: "*Communication is essential in this sense because it is a key to solve the problem of mistrust, preconceived ideas on AI implementation. This kind of communication will promote the idea that employees are more valuable than AI*".

Interviewee 3: "*Open dialogue between managers and employees is the best recipe for integrating these systems in ways that actually enhance the quality of work*".

Table 4. Themes identified for Research Question 2 (RQ2) (Third article)

S. No.	Themes	Frequency	Percentage
3.1	Create communication channels	28	19.4
3.2	Enhance the awareness of the positive impact of AI on employee performance	17	14
3.3	AI-employees collaboration maintains a balance among job demand, professional development and social life	9	8.5

Note: Only the themes with a frequency of more than 2 were included

Another dominant theme was enhancing awareness about the positive impact of AI on employee performance (14%). AI plays a role in accelerating the achievement of employees' daily tedious work by providing a powerful database and analytical support for their decisions. To rule out alternative explanations, the dominating idea spread among employees that AI-powered solutions are machine-oriented and have difficulties in understanding human perceptions. To eliminate negative perceptions, HR managers should offer practical evidence to convince employees about the ability of AI-powered solutions in customized recommendations depending on the demanded tasks. Quoted below are some instances from the interviewees' answers:

Interviewee 1: "*HR managers should make employees aware about the usefulness of AI; it's here to support them, not to disturb them, as well as sharing the message that employees could promote themselves by focusing on developing their skills. On the one hand you improve your performance and, on the other hand, it could minimize your routine*".

Interviewee 2: "*Promote awareness with real examples. For instance, if you would like to speak with HR staff, obviously you have to talk during working hours. But if you're talking to AI-powered chatbots you can talk at night once you're back home after work. So this atmosphere should be dominant among employees. AI minimizes employees' routine tasks and maintains the organization's repetition*".

Therefore, employees collaborating with AI maintains the balance among job demand, professional development and social life (8.5%). AI is led to constantly change in the jobs conducted by employees. Combining the rapid speed of AI development with changes in employees' lifestyles gives a balanced job-social life a whole new meaning. AI implementation will offer employees new opportunities to develop their skills and to spend time with their families as a result of achieving deadlines more quickly. Therefore, sharing the message with employees that AI compliments human productivity and, unlike the normal perception, poses no threats, will facilitate AI implementation strategies. Quoted below are some instances from interviewees' answers:

> Interviewee 8: "*We have to build confidence. What is the benefit of the intention of using new technology? We should send to employees the notion that AI reduces their workload and helps to strike a balance between job demands and social life demands. This kind of balance will add value to their job and family. On the one hand, relieving employees from tedious tasks and providing them with easier access to information. On the other hand, employees will have time and effort to invest in their children and family. It's about these kinds of benefits and how they will impact their lives, and not about taking their job away but, instead, AI will reduce their work so they can concentrate on somewhere else*".

> Interviewee 2: "*HR managers have to share the message that AI is here is to support employees and for them to reach their targets, which will definitely be reflected on social life*".

These results fall in line with the findings reported by Dabbous et al. (2021), who claimed that employees' acceptance of new technologies depends on several factors. Individual factors are major determinants of employee acceptance. They also added that organization social environment, culture and HR strategy are technology acceptance parameters. Therefore, HR managers should integrate organizational culture, social environment and technology acceptance factors when implementing AI-powered solutions.

Discussion

The present study makes some significant contributions with consequences for both research and practice. This section highlights the areas in which we extend current knowledge boundaries and the ramifications of our findings.

Research implications

Several studies in the academic literature have dealt with the relation between HR managers and emerging technology. Previous scholars have identified the crucial role of AI techniques in HR manager activities, such as supporting complex HR managerial decision making (Reddy et al., 2019) and assisting HR managers in performing productive big data analyses to achieve desired outcomes (Qamar et al., 2021). In contrast, other scholars have advised HR managers to update their technical skills and enhance their knowledge in data privacy and AI ethical issues (Stahl et al., 2021). These skills play a role in spreading "AI-enabled-HR services" technology (Qamar et al., 2021).

Scholars have also been advised to identify the keys that facilitate leveraging the AI- powered applications in HR tasks (Fernandez & Gallardo-Gallardo, 2021). In line with this, the present study performed an in-depth analysis to understand the key elements for transferring knowledge of the AI implementation process to HR managers. The findings identified the following challenges associated with AI implementation: potential risk resulting from data shortage; ambiguous vision of the emerged technology; mistrusting AI recommendations leads to fewer advantages of AI applications.

According to these results, companies that seek to adopt AI solutions in HRM should pay attention to these elements to ensure the successful knowledge transfer about the AI implementation process. In order to do so, they should: 1) offer intensive training programs for HR managers that cover the AI implementation process, 2) assign AI specialists to follow up implementation progress and to eliminate any potential collapse in AI-powered solutions.

After the present study performed a detailed analysis of the key elements to transfer knowledge about AI implementation processes, it provides a comprehensive view of the COVID-19 impact on AI implementation. There are many advantages from accelerating AI implementation during a pandemic. However, this usefulness is affected by the potential threat associated with an AI bias to the performance of both employees and organizations. Prior research on AI implementation during COVID-19 has demonstrated that making investments in AI can represent a successful approach to limit disruptive impacts (Acciarini et al., 2021). Accelerating AI implementation may enhance employee welfare in many ways, such as improving productivity, performance and learning. However, AI misuse due to an algorithm bias and lack of governance could inhibit employees' rights and result in a high turnover, customer dissatisfaction and employee retention (Yang et al., 2021).

Second, this paper presents the steps carried out by HR managers to ensure smooth AI–employee collaboration. The study proposes a list of factors to ensure positive collaboration, such as: establishing communication channels; highlighting the positive impact of AI on employee performance; examining the role of AI in maintaining employees' job demands, professional development and social life. Prior research works have indicated that AI-powered technology interventions are seen as being relatively complex, and does not pose a challenge only for an organization to implement it, but is also difficult for employees to accept it (Dabbous et al., 2021). It is HR managers' responsibility to spread to employees a sense of trust, morality, transparency and value in relation to AI (Papagiannidis & Marikyan, 2020). This effort depends on collaboration across several departments because the premise behind AI implementation is not to replace employees, but to enhance employee performance. A high transparency level is particularly important when new technology affects the HR process (Lichtenthaler, 2020).

Practical implications

AI implementation processes consist of data input (e.g., software-readable data of employees' attitude and performance); data analysis (e.g., analysis of the structure and unstructured data); results generated from data analyses (e.g., information, statistics or predictions) (Meijerink & Bondarouk, 2021). Thus HR managers need to understand the functionality of each stage and improve their technical skills to obtain utilitarian benefits from AI-powered solutions. For instance, acquiring essential knowledge on data mining, programming, big data analytics and robotics could be the backbone of emerging AI technology (Pereira et al., 2021). These skills will help HR managers to understand the AI implementation process and, at the same time, to protect AI specialists from any potential employees' resistance to AI applications affecting and eliminating their decisions. For instance, one requirement of a new AI system involves making certain modifications to the job specification and performance appraisal system, which may bring about mistrust of an organization's decision making if it is performed by an AI specialist instead of the HR manager.

The advantages of HR managers acquiring essential knowledge of the AI implementation process are not supporting their decisions on employees, plus their productivity during crises and pandemics. COVID-19 and the consequences of lockdown have threatened companies in different ways, such as sacking many employees, losing financial funds and income, and changing the workplace structure. AI has acted as a magic wand to solve most of these up-normal circumstances. Companies with a higher AI maturity level have greater flexibility to adapt to these challenges by protecting employee well-being, having personalized internal communication, reducing costs and providing differentiated user experience (Abed, 2021). To leverage AI-powered solutions, organizations have to be aware of managing different types of AI risks, such as: 1) insufficient data security precautions; 2) insufficient data analytics processes; 3) AI scripting errors; 4) lapses in data management; 5) misjudgments in the training data model (Cheatham et al., 2019).

The AI training data bias is considered another type of risk that is reflected on the whole performance of both employees and the organization. A training data bias may come from algorithms, data input, or from the interaction between both (Sun et al., 2020). Ignoring potential risks associated with AI implementation can easily compromise employees' fairness, privacy, security and compliance.

Second, motivating employees toward using AI should be driven by practical incidents. For instance, combining the speed of AI to collect and process data and to achieve employees' tasks and responsibilities are drivers to minimize employees' resistance to AI implementation (Jarrahi, 2018). Demotivating employees toward adopting AI applications could harmed AI functionality in two ways: through non cooperation and data obfuscation (Newlands, 2021). Non cooperation entails ignoring AI directions and recommendations. For instance, AI is able to boost employee productivity by recommending various solutions to a single problem. Ignoring these recommendations may affect the overall performance evaluation. Data obfuscation is described as any process that hides sensitive data while retaining certain aspects of usability. For example, when employees create an alternate version of data that is not easily identifiable or reverse-engineered they, therefore, seek to manipulate the generated results using AI-algorithmic control mechanisms (Kellogg et al., 2020). HR managers have to deploy a sequential AI implementation process by first selecting pilot employees, followed by analyzing the reflection of AI solutions on the selected sample and, finally, deploying training with a wide range of employees. The symbiotic interaction between employees and AI solutions is critical for successful AI implementation (Grover et al., 2022).

Conclusion

The evolving and mutual relation between the implementation of emerging technologies and the HR process can be lucidly explained by an in-depth qualitative study. This exploratory study builds on two recommendations made by Chang (2020), namely: 1) key factors in the successful knowledge transfer of the AI implementation process to HR managers; 2) HR managers' strategies for smooth AI implementation among employees. By building further on these earlier contributions, we offer a deep understanding of the challenges associated with AI implementation into the HR process and the impact of COVID-19 on AI implementation. These contributions help in building the key elements to transfer knowledge of AI implementation processes for HRM in COVID 19 times.

Such a study provides a comprehensive understanding in addition to the considerable existing literature on AI implementation and the AI-HR managers-employees interaction. The study is one that focuses, on the one hand, on the challenges that affect AI implementation and, on the other hand, on particular strategies for managers and employees to undertake digital transformation.

The bottom line is that this study's findings provide valuable details for AI developers and HR managers when digitalizing the HR process. It calls for a wide range of organizational activities that come in the form of developing HR managers' technical and soft skills, such as data analysis, digitalization trends, basic AI core concepts, communication skills, critical thinking, team building and leadership skills. All these soft skills are lifesavers in today's technology-driven environment because they allow employees to accept HR managers' guidance to implement emerging technologies (Caputo et al., 2019).

Limitations and future research

The present study is subject to limitations. Due to the novelty of this study, a qualitative study was performed and the sample of respondents is relativity small. Using different meta-analyses and extending the number of interviewees could generate new areas to transfer knowledge about the AI implementation process.

Different future research works could be carried out in several directions to open up new avenues for the complex interrelations among AI transformation, management and employees. For instance, examine if HR managers' academic background could become the key factor for successfully transferring the AI implementation process. Second, analyze if HR managers with IT experience have enough skills to cover the needs of the AI specialists in their organization. Third, empirically validate the impact of transparency against employee fears toward AI implementation. In addition, it will be interesting to test moderate factors, such as employees’ age, experience, seniority and academic background, and their influence on HR managers accepting activities toward smooth AI-employee collaboration.

Bearing in mind the fear of the unknown that has been raised from the AI bias, future research could investigate the legislation and constraints on AI-trained data, as well as the level of dependence on AI’s judgment for employee professional development-related issues.

5. Conclusion

Efficient HRM is not only facilitating HR activities but also a strategic partner opening a new ground for analyzing, predicting and boosting performance by integrating employee databases with the organization's goals. Employing emergent technologies such as AI is balancing this formula and restructuring the functionalities of HRM.

Every story has two sides, so does AI in HRM. Nowadays, more and more HRM functions are being controlled by massive databases typically empowered by AI. The motivation for adopting AI is clear, we expect AI to perform better than employees due to several reasons: First, AI may integrate much more data than employees may realize and take many more considerations into account. Second, AI can perform complex calculations much faster than employees. Third, AI applications can better deal with low-end predictable and routine tasks from the employees.

While the promises of AI are encouraging employees' performance and helping HR managers in managing and predicting this performance, its potential dark side may also present. Uncertainty is a determinant factor that can lead to a lack of trust and enforces negative perceptions towards AI outcomes in HRM. These can pave the way for the emergence of a series of dark sides (Kambur & Akar, 2021). In details, AI uses data from different sources and thus poor data management may be used to manipulate the choices and decisions of employees and organizations. The influence of wrong AI's recommendations not only hinders employee performance but also has a considerable impact on organizations' decision-making quality. In this regard, the dark side of AI may be associated with the negative employees' perceptions, such as inequality, lack trust towards AI-based decisions, lack of transparency and bias. From this perspective, the acute shortage of accurate perceptions towards AI in HRM may pose a threat to adopting intelligence-based technology in HRM.

HR managers with inappropriate understanding of the conceptual meaning of AI in HRM may cause HR's business to progress in a negative way. In addition, unrecognizing the advantages and disadvantages of the commonly used AI applications in HRM may invite risk in adoption. Along similar lines, the solutions of AI to be used in HRM should be accurately conveyed to HR managers and employees. HR staff without sufficient knowledge of the AI implementation process may raise the dark side and risk associated with the AI integrated into HR goals.

In order for HR staff to leverage AI applications, there is a need to avoid the dark side of AI in HRM. The present thesis originally addresses the above-mentioned need by conducting different research methodologies on AI in HRM. Therefore, the key aim of this thesis is to take a closer and critical look to identify the actual status of AI in HRM through 1) building a conceptual definition of AI in HRM; 2) identifying the most dominant AI application in the HR process; 3) analyzing challenges associated with AI implementation in the HR process in COVID-19 times; and 4) facilitate AI's implementation process for HR managers and employees.

As far as the first concerns, SLR has been employed and guided by other previous systematic studies to drive AI definition in HRM. AI in HRM defines as a technology that consists of machine learning and deep learning, capable of mimicking human cognitive activities to achieve HRM practices. This definition is built based on the existing literature and it takes into account two approaches: previous AI definition and advantages of AI in HRM. This definition considers a foundation to boost HR managers' understanding in aligning the features of AI in HRM practices and strategy.

Also, it concludes that recruitment and talent acquisitions are the most dominant area for AI applications. AI can analyze volumes of data to find suitable candidates, through scanning the social network and assessing the candidate's knowledge, experience, values and beliefs. In details, AI can automate functions such as designing job descriptions, sending vacancies to potential candidates, providing technical support through chatbots, and facilitating decision making. Also, it reveals that other applications have been used widely in HRM such as ML, NLP, expert system and fuzzy system. All these applications are bringing radical changes to the way HRM practices influence business operations in organizations. However, the literature fails to build a clear framework for adopting these applications in HRM.

Other results concluded from the SLR that the implementation of AI in HRM has not been thoroughly investigated by researchers yet. In spite, the implementation strategies of AI in another management area (such as marketing) have been developed and discussed widely in the literature. While this thesis demonstrates the usage of AI in HRM to some extent, the findings suggest that this context has been little discussed so far by academics and still poses unanswered issues and concerns.

In line with the second concern, qualitative analysis has been employed and the result reveals that chatbots in recruitment are the most advanced AI-powered solutions in HRM. It considers as the core advanced technology in the field of NLP. Chatbots offer immediate responses with candidates, employees and external clients. Apart from that, chatbots are saving time/cost and minimizing wasting efforts; minimizing bias within the recruitment process; positive candidate experience; and guarantee the performance of the hired employees. These advantages help HR staff to reduce the workloads, they can just observe and decide to whom they will be calling without investing hours in hundreds of unqualified candidates.

The striking thing about the chatbot in recruitment is improving HR department productivity. However, this thesis concluded several obstacles which may affect the future of this technology. First, there is a gap between what are IT companies offering for recruiters and what are recruiters know about the latest development of chatbots in the market. Second, Up to date, chatbots for hiring a mid-level and senior-level are not useful. Third, Up to date, chatbots have difficulties in extracting information from CV correctly. Fourth, algorithm bias is one of the biggest threats to the future and potential of chatbots in recruitment.

Due to the fact that chatbots in recruitment are still an emerging technology, two dimensions may determine the future of this technology. These dimensions are: A) the ability of chatbots in dealing with the unstructured script; and B) the ability of voicebot to replace text conversation dialogue.

In terms of the third and fourth's concern. By using qualitative analysis, this thesis formulates deep conclusions for the key elements to transfer knowledge of AI implementation processes for HRM in COVID-19 times. These elements are: challenges related to implementing AI into HR processes; transferring knowledge of the AI implementation process to HR managers; HR manages' strategy for smooth AI - employees interaction. In terms of the first element, the results of the research reveal that shortage of employee data, ambiguity in AI decision framework, manager's desire to bypass AI decisions, weak infrastructure, limited integration between departments are the most challenges affecting AI implementation in the HR process. Eliminating these challenges could have a major influence on fostering AI implementation among HR managers and employees. In the parallel line, as far as COVID-19 concerns, the outcomes of this thesis reveal that accelerating in adopting AI during Covid-19 has no negative impact on organization performance. However, the organization should consider the threat associated with AI bias when adopting AI technology. Ignoring the potential risks associated with AI bias can easily compromise employees' fairness, privacy, security and compliance.

HR managers need to understand the functionality of each stage of the AI implementation process, thus improving their technical skills are the key to obtaining utilitarian benefits from AI-powered solutions. This thesis concluded that organizations should offer for HR managers intensive training programs on the features of each stage of the AI implementation process as well as assign AI specialists to eliminate uncertainty in AI functionality.

In terms of the third element, this thesis reveals that HR managers should carry out several steps to ensure smooth AI–employee collaboration. These steps are : establishing communication channels with employees; highlighting the positive impact of AI on employee performance; examining the role of AI in maintaining employees' job demands, professional development and social life. All of these steps are helping HR managers to spread a sense of trust, morality, transparency and value of AI solutions among employees. This effort depends on collaboration across several departments because the premise behind AI implementation is not to replace employees, but to enhance employee performance. A high transparency level is particularly important when new technology affects the HR process.

In summary, all results show that the development of AI in general and its adoption in HRM is progressing rapidly. Research has not yet been able to keep pace with this and must catch up quickly. Since this topic involves several research disciplines, there are plenty of opportunities for deeper research at the points where the topics overlap.

This doctoral thesis, or rather the cumulated articles, contributes a small part to identify the actual status of AI in HRM. Furthermore, it demonstrates the fact that AI in HRM solutions are significant and keeps growing rapidly.

6. Future Research

This thesis also offers important avenues for future research. First, future studies could analyze the potential area of AI-algorithm bias in HRM functions and the impact of this bias on employee performance. Furthermore, the mechanism to detect and prevent AI-algorithm bias. The scope of AI-algorithm bias in future research could be examined from two perspectives : organization and employees.

In terms of the organization's direction, the questions listed below could guide future research:

1- What are the economic consequences of AI bias on organization investment and assets?
2- What are the perceptions of the critical stakeholders (such as recruiters, managers, frontline employees, and customers) on the potential AI bise?
3- How are critical stakeholders' cognitive processes affected by the AI bias?
4- How can organizations track the influences of AI decisions to minimize the negative impact of AI bias?
5- how should organizations structure their business and technology architectures to support data engineering and avoiding AI bias?
6- How can an organization ensure the quality of data is sufficient to support the required analysis and avoid AI bias?
7- Under what circumstances and to what extent can organizations rely sufficiently on the sets of integrated AI components based on different data?
8- Under what circumstances do organizations require transparency of reasoning and how can this be delivered when AI components are integrated?
9- How are decisions made regarding AI-enabled automation to avoid AI bias?
10- Is the substantial cost of developing and implementing AI techniques may affect by AI bias?

For employee’s direction, the questions listed below could guide future research:

1- What is the effect of AI bias on employees’ emotions after the change in the nature of the workplace?
2- How to balance the competing interests of innovative data use and personal data privacy rights?
3- Could machine using AI become depressed and have other human-like psychological problems?
4- Do we need employees to effectively monitor and respond to AI-enabled automation errors and bias?
5- What is the impact of biased hiring algorithms on the perceptions and behaviours of underrepresented groups?

Second, several advancements of AI in HRM functions (video interviews, virtual reality-based inductions, etc.) generate diverse forms of data (unstructured data such as videos, charts, graphics, pictures, text, etc) which can be made more useful using the relevant AI application. Therefore, future research could analyze employees' perception, both skilled and semi-skilled, towered collecting data and utilised emerging technologies such as AI in tracking employee productivity and performance.

Third, through our research, we seek to shine a light on the role of HR managers in smooth AI-employee collaboration. This role is prominent to grow, not only employee experiences and performance. But also, the digitalization within the workforce and the evolution of AI within HRM functions. From this perspective, key decision-makers and boards could have a critical role in implementing and utilising AI. Thus, future studies need to examine the leadership styles conducive to utilising AI in HRM. For instance: What is the role of leaders empower in promoting AI implementation within employees?; What is the difference between participative leadership style and authoritarian leadership style on accepting AI-powered decisions?; Does leadership style is affected by the gender and education of employees and how could these changes affect adopting AI in HRM?

Finally, through our thesis, we highlight that AI training-algorithms is fueled by employee's data. This data could be collected to cover employees' activities inside or outside the organization. Thus, future research could analyse the main sources of the employees' data set. Should we use only internal employees' data set to feed AI-algorithm applications? Or we could import external templets of the employees' data set, followed by highlighting the advantages and disadvantages of both of them. Further questions could arise in this area to cover : who has the authority to maintain related data ethics like shared data, accuracy, completeness, and privacy concerns?; how should organizations attempt to enforce employee privacy with maintaining the functionality of AI-powered solutions ?; When AI systems become smarter than the employee, will organization lose the control on the data source and privacy ?.

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8. Appendix

The determinants of employee’s performance: a literature review

Title:	The determinants of employee’s performance: a literature review
DOI:	10.30560/jems.v3n3p14
Format:	Journal Article
Journal:	Journal of Economics and Management Sciences
Language:	English
Status:	Published
Keywords	Performance, knowledge management, information and communication technology, empowerment, innovation and creativity, productivity.

Abstract

This piece of research highlights a contextual understanding of factors affecting the employees' performance in the organization. Through analyzing the literature of ISI (Web of Knowledge) from 2015 until 2019, after that, extract determinant elements influencing employee performance. Results show that managing employee performance brings new opportunities for Human Resource Management (HRM), but also challenges at the technological and methodological level. This study reveals that knowledge management, information and communication technology, employee empowerment, innovation and creativity, and organizational culture are the determinants of employee performance. The academic contribution of this paper and the future research avenues are outlined.

Introduction

Companies and organizations should focus on building employees' positive performance by providing them with a group of tools and skills to meet new realities and challenges (Batarlienė et al., 2017). Globalization, new market demands, innovation and smart economies are considering a challenge, as well as driver for companies to maintain and improve employee performance (Cooper & Ezzamel, 2013). Quick changes in technologies, stakeholders' requirements and market demands are encouraging HR managers to reduce the gap within employees' attitudes in order to achieve the organization's goals (Shah et al., 2017).

Researchers have defined employee performance as well as highlighted parameters affecting employee performance as the following. Anitha.J (2014) reports that the performance of individual or organization depends on the sound structured organizational activities, policies, procedures, knowledge management and employee engagement. These elements are vital determinants fostering high levels of employee performance. Along similar lines, Islami et al. (2018) argue that managing performance is a planned process in which the key elements are agreement, measurement, support, feedback, and positive reinforcement, which shape employee performance outcomes. Also, Bataineh (2017) highlights employee performance as a combination of efficiency and effectiveness of the employee's daily tasks to meet the stakeholders' expectations.

Isaac et al. (2017) show that employees highly agree about the role of technology in accomplishing daily tasks, enhancing their knowledge and facilitating communication between departments, leading to improving individual performance and organization. In parallel, Pawirosumarto et al. (2017) tide between employee performance and work environment that consist of physical and non-physical factors and have a reflection on employee performance. These factors are considered a new paradigm that may subscribe to reshape the model of employee performance (Smith & Bititci , 2017). Mensah (2019) supports the same idea by emphasizing on talent management as a critical success factor within companies. Improving the strategy of talented employees is the most core managerial value in our highly dynamic and uncertain market in the twenty-first-century era.

Based on these observations, this paper aims to enhance the literature by understanding the determinant factors affecting on employee performance. This study proposes a conceptual model; consisting of five factors: knowledge management, information and communication technology, employee empowerment, innovation and creativity and organization culture (de Menezes & Escrig, 2019). Furthermore, this model will identify the correlation between these factors and their impact on employee performance.

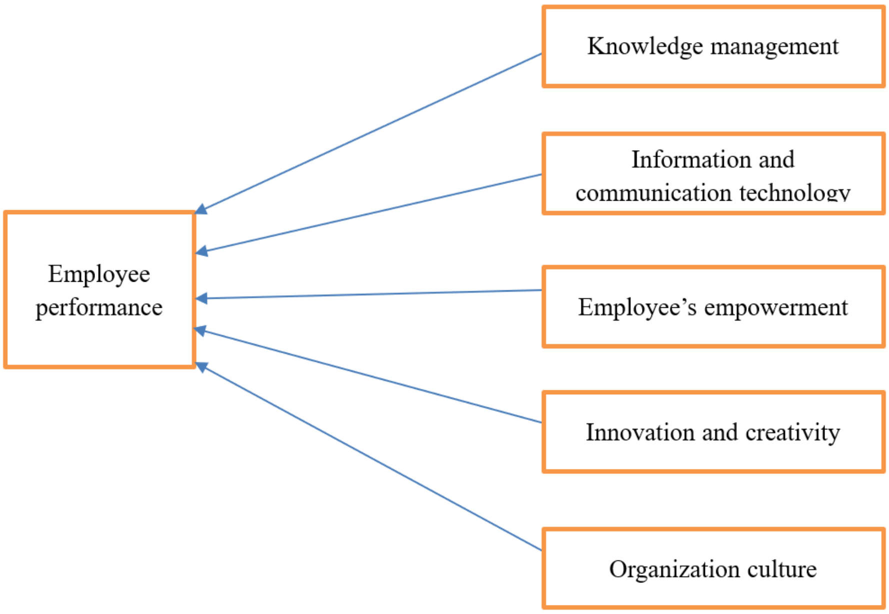

Figure 1. Factors affecting employee performance

Methodology

A systematic literature review (SLR) aims to present a fair evaluation of a research topic by using a reliable, efficient and trustable approach (García-Holgado et al., 2020). The author analyzed journals in ISI (Web of Knowledge) between 2015 and 2019. While selected articles are corralling with keywords of employee performance, knowledge management, information and communication, empowerment, innovation, creativity and organization culture. The correlation among the variables is based on a meta-analysis. Furthermore, the Boolean logic (i.e. AND or OR) was used to express relations between search terms and extract relevant articles.

This paper follows the proposed of García-Holgado et al. (2020) for conducting SLR: 1) formulate the research questions and the search strategy; 2) filter and extract data based on inclusion and exclusion criteria; 3) synthesizing the findings. The resulted papers of SLR aim to explore the answers for the following questions:

1) What are factors affecting on employee performance?

2) Is there a correlation between these factors?

Findings

Knowledge management and employee performance

Knowledge management (KM) has gained huge attention during the past few decades, as researchers have recognized the importance of managing knowledge in a knowledge-based economy (Ali et al., 2019).

Scholars have defined KM as a concept that depends on collecting, auditing and sharing information within the organization's stakeholders (employees, customers and partners). Susanty et al. (2019) claim that KM is a learning process that explores and shares knowledge supported by optimum technology and cultural environment. Promoting the integration and collaboration approach in the overall organization department leads to create the enterprise's knowledge assets. These assets could intend to develop KM systems that provide enterprises with machines and tools to restructure and manage employees' knowledge, depending on technological and social components across overall departments of the organization, which is well-known recently as "socio-technical systems" (Hwang et al., 2018).

This system enhances enterprises' utilizes such as organizational learning and quality management, which lead to sustainable competitive advantages (Gunjal, 2005).

The result of the investigation on the relationship between KM and employee performance is positive in the literature. This positiveness appeared in four phases of the KM process, which are: 1) knowledge creation, 2) knowledge capture and storage, 3) knowledge sharing and 4) knowledge applications (Ahbabi et al., 2019).

Organizational performance depends on specific elements that consist of organization reputation, employee satisfaction, customer loyalty and market share (Imran et al., 2018). The core of the previous combination depends on knowledge sharing that is considered an essential tool to achieve the desired expectation of knowledge management. It's strongly believed that organizations' survival and success depend on sharing skills, knowledge and experiences within employees (Soto-Acosta et al., 2017). In other words, helping employees create new knowledge and motivating them with unique learning abilities will promote the culture of creativity and innovation in the organization, which influences employees' attitudes, behavior, skills, and performance (Jogaratnam, 2017).

KM infrastructure is a critical element in the knowledge management process. This result appeared when examining the positive relation of KM infrastructure (Organizational Culture, IT Infrastructure, and Organizational asset) on the KM process and how the knowledge management process is significantly related to employee performance (Almajali & Al-Lozi, 2019). Knowledge management infrastructure contains two factors: technical infrastructure and social infrastructure. Where, on the one hand, technical infrastructure includes information technology (software), tools, and hardware. On the other, social infrastructure includes organizational culture, organization structure and human resources (Abualoush et al., 2018). Another critical element in the KM process is a performance management system that tracks the implementation of organizational strategic objectives by evaluating individual performance (Sales, 2019).

Information and communication technology and employee performance

The wide diffusion of information and communication technology (ICT) has strongly impacted the organization's dynamism. ICT facilitates abroad range of organizations' activities related to production, marketing, customer loyalty and employee performance (Reichstein, 2019). ICT transformed the nature of products, companies and the market's competition. In detail, Giotopoulos et al. (2017) report that integration between ICT and organization strategy directly reflects on organization and employee effectiveness, cost-saving, and opens new markets.

The influence of ICT started in 1990, when experts compared the productivity growth of companies located in Europe and the USA. It's noted that American companies win the competitive advantages by using ICT widely in various economic sectors (Melián-González & Bulchand-Gidumal, 2017). These sectors are recently affected by Internet of things (IoT), cloud computing and data analysis. Caputo et al. (2019) report that the spread out of social networks, virtual realities and artificial intelligence (AI) in the organization could enhance the impact of ICT. For instance, AI could support the processing of business intelligence tools and enhance productivity (Caputo et al., 2019).

Human Resource Management (HRM) is affected dramatically by ICT. It transformed the way of collecting, storing, analyzing and evaluating employees performance (Turulj & Bajgoric, 2018). The strategic approach of integration between HR and information technology lead to develop E-HRM. Irum & Yadav (2019) explain E-HRM as a combination of computer programs, software tools, databases, and hardware to record, store and analyze data of the Human Resource (HR) applications. The organization portal is considered an interface of E-HRM, which consists of ERP, Enterprise Intranet Portals and Business-to-Employee Portals. These portals serve different purposes like performance analysis, knowledge sharing and virtual employee communities (Ali et al., 2019).

Many scholars highlighted the advantages of E-HRM. For instance, Rahman et al. (2018) claim that E-HRM works as an analytical tool helping the decision-makers in constructing an accurate decision that leads to improve HR functions and employee performance. In detail, Obeidat (2016) mentioned E-HRM as a supportive tool to improve the productivity of an organization through the customized personal development plan, rewards allocation and performance appraisal.

E-HRM's achievement marks a significant milestone in the relationship between employee performance and ICT. Tabatabaei et al. (2017) emphasize on ICT as the primary source for sustainable employee performance by facilitating knowledge exposure, improving skills and sharing experiences. Furthermore, ICT had a role in recruitment and selection, performance appraisal and workforce planning.

Employee's empowerment and employee performance

The literature explains the employee's empowerment as top-down hierarchies of influence, with client/designer dominating, and bottom placed labourer/employee having nominal input to management activities (Alazzaz & Whyte, 2015). These activities are enhancing organizational competitiveness and associated with the organization's knowledge sharing, rewards systems and employee performance (Potnuru et al., 2019).

García-Juan et al. (2019) identify two different perspectives to understand employee empowerment. First one is a structural perspective that contains a set of practices and policies that enable to transfer the power and authority from the top to the bottom in the organization. While the second one is the psychological perspective that concerns employees' attitudes in reaction to managerial practices.

Empowering employees is critical in today's competitive environment where organizations are affected by globalization, rapid market changes and new customers demand. These challenges are required innovative and creative solutions that rely on empowering employees to meet these challenges (Shah et al., 2019).

To enhance the level of empowerment in the organizations, management should expand communication with employees to make sure that employees are aware of the organization's mission, vision, value and desired targets of each individual (Baird et al., 2018). Empirical studies point out that management can promote empowerment by engaging employees in decision-making and organization objectives (Nayak et al., 2018).

This part of the literature investigates the theoretical relationship between employee performance and employee empowerment as a central factor affecting organization survival. These factors are affecting on employees satisfaction, reduce job-related strain and minimize employee turnover.

Innovation, creativity and employee performance

Many organizations are recently fighting to survive in rapid economic changes by developing and understanding the factors that promote the culture of innovation and creativity within employees. Therefore, many scholars have concluded that innovation and creativity are crucial in daily tasks. In this part of the study, we particularly looking upon the relationship between employee performance and innovation and creativity. Also, the ways to implement strategies that support innovation and creativity in the organization.

Many scholars have been discussed innovation and creativity and highlighted the critical role of innovation and creativity in future organization success. They identified creativity as a process of idea generation and implementation toward better procedures, practices, or products (Olsson et al., 2019). While, innovation refers to applying new and valuable thoughts in the workplace (Khalili, 2018). Creativity is the generation of novel and valuable ideas or solutions, while innovation is the actual implementation and execution of creative ideas (Kremer et al., 2019). Creative workplace concerns the cognitive and behavioral processes applied when generating novel ideas. Innovate workplace concerns the techniques used when attempting to implement new ideas (Hughes et al., 2018).

The question appears which one is coming first, innovation or creativity. According to Khalili (2018), creativity is a fundamental step in innovation. Kremer et al. (2019) agreed with Khalili when they were concerned about the existence of innovation depending on creativity. Promoting innovation within the organization passes through several processes, starting with the decision to innovate by budgeting investment. Then commercialization of original ideas, after that prepare an adequate work environment that motivates staff to create unique ideas depending on human, physical and intellectual resources. Therefore, creativity developed through stages that involved preparation, generation and validation of ideas and assessment of achieved outcomes (Stojcic et al., 2018). Promoting the culture of innovation and creativity within employees depending on four pillars. Firstly, leadership is considered the first component that works on creating the next level of leaders, not just followers. Promoting leadership culture is being the role model of innovation, co-creation and fostering innovation. The second pillar is employee, as a source of innovation and creativity by encouraging the maximum potential of employees through involving them in decision-making as a clear internal motivation strategy. Capability building is considered the third pillar that depends on internal capability investment by aligning several interrelated elements and assets. The last pillar depends on developing a model of innovation outcomes (Olsson et al., 2019).

Fostering innovation and creativity in the organization has numerous benefits and positive consequences on employee's psychology, behavior and performance. These benefits will reflect on the organization's financial performance (Nguyen & Le , 2019).

Organization culture and employee performance

The literature explains the importance of organizational culture on overall organization's performance by referring to Hofstede's theory (1965) as a reference point to explain four dimensions of culture which are power distance, uncertainty avoidance, individualism and collectivism and masculinity and femininity (Mahadevan, 2017). In this paper, we are highlighting the relationship between employee performance and organizational culture.

There are numerous definitions of organizational culture. Nikpourm (2017) defines organizational culture as the pattern of beliefs, values, and experiences reflecting on material arrangements and members’ behavior. Where Shahzad et al. (2017) refer to organizational culture as an employee's values, and beliefs shared at all levels and displayed of organizational traits.

Researchers widely categorized organization’s culture into three types, innovative organizational culture (IOC); bureaucratic organizational culture (BOC); and trust and supportive organizational culture (TOC) (Wu et al., 2019). IOC is represented by a work environment that is creative, results-oriented, and challenging. This dimension involves an enterprising and opportunity-seeking environment that attracts employees to solving challenges and risks. BOC refers to an organized, systematic, procedural, and regulated work environment. Organizations with high on this dimension lack flexibility and emphasize efficiency, predictability, and consistency. TOC is manifested in a work environment that is trusting, people-oriented and encouraging. Such a culture facilitates relationships among employees and provides an equitable, friendly, and helpful workplace (Jogaratnam, 2017). In this review, we are focusing on the influence of an innovative culture.

To build a creative culture, researchers have been described elements that figure out organizational culture. Emerging technology, Teamwork, communication and training and development are the main pattern of organizational culture (Ramdhani et al., 2017). While Rich et al. (2018) mentioned innovation, orientation outcome, aggressiveness, stability, attention to detail, respect for people and team orientation as main elements of organizational culture. Also, Wu et al. (2019) agreed with them when they mentioned compliance, leadership, decision making, effectiveness and values as elements of organizational culture.

Most scholars agreed that organizational culture is a magic stick “ recipe” that positively influences organization attitude and business improvement (Mahadevan, 2017). This positiveness expands to reach, not only, employees and organization performance but also organizational commitment (Nikpour, 2017). It’s important to highlight that, organizational culture is linked with updated technologies. It’s served as a key for satisfying employee performance, moreover an engine for promoting the culture of creativity and innovation in the organization.

The correlation between organization culture, knowledge management, information and communication, employee empowerment and innovation and technology from one side and their impact on employee’s performance from the other side is clear. The organizations that build their strategy on adopting a correlation between ICT and innovation and creativity have a significant influence on employee performance. This assumption is supported by several researchers starting by Ndou et al. (2019) when they argued that creative economy progress is measured in terms of human capital performance against implementing clear strategies that maintain information communication technology and innovation and creativity. The same result is concluded by Laar et al. (2019) when they identified that creativity, communication, collaboration, and analytical skills are presented as major skills for the professional employee.

Conclusion and Limitation

A broad literature explained employee’s performance and the factors influencing this performance. Therefore, this conceptual study contributes to enhancing understanding of factors impacting on employee performance.

As shown in this research, several factors are affecting on employee performance. First, organizational knowledge management has a significant role in improving employee performance by analyzing employees' current skills, knowledge, and ability, then designing a proper strategy to reduce the gap between the present and desired performance. Second, ICT is considering the core assets of the organization that is working to encourage employees to improve their performance. The third factor is empowerment, which has a tremendous impact on an employee’s performance to reshape the organization’s attitude in dealing with numerous challenges and threats in the market, especially if the organization is looking for their employees as a competitive advantage for surviving. Fourth, creativity and innovation are playing as change agents in promoting a new idea, which leads the organization to face uncertainty and complexity in a highly changing environment. The fifth factor is organizational culture, which works as an umbrella that drives employees’ performance to develop creative solutions.

Recently, ERP is adopted as a functional arm that facilitates the process of collaboration between technology, organizations and employees through involving them in managements concerns, strategic goals and targets, self-learning and knowledge management.

The main limitation of this research is being conducted depending on one database within a limited period, between 2015 and 2019, which influences the accuracy of information. Future research should increase the size sample to collect more data regarding the factors affecting an employee’s performance.

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Adoption factors of artificial intelligence in human resource 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.

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 advanced development in HRM technologies (IBM, 2020).

These technologies are facilitating the implementation of big data analysis, machine learning and deep learning in the HRM (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 (Chen, 2019). It refers to a trained machine intelligent to perform tasks like a human. Wang and Siau (2019), 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 et al., 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 et al. (2018). They claimed that organizations can take the 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 et al., 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 to determine the best candidates who potentially fit with the organization's demand (Vinichenko et al., 2019). All of these could be done without human intervention.

Another example of advantages of 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 of advantages of 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 in commercial sectors, probably, due to the fact that the driving factors for AI adoption in HRM are still unclear (Lengnick-Hall et al., 2018).

Overall, this piece of research aims at identifying and analysing adoption factors fostering of 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 AI adoption (Chen, 2019), and scenarios of AI in HRM (Strohmeier & Piazza, 2015) are discussed, as it could be seen in figure 1.

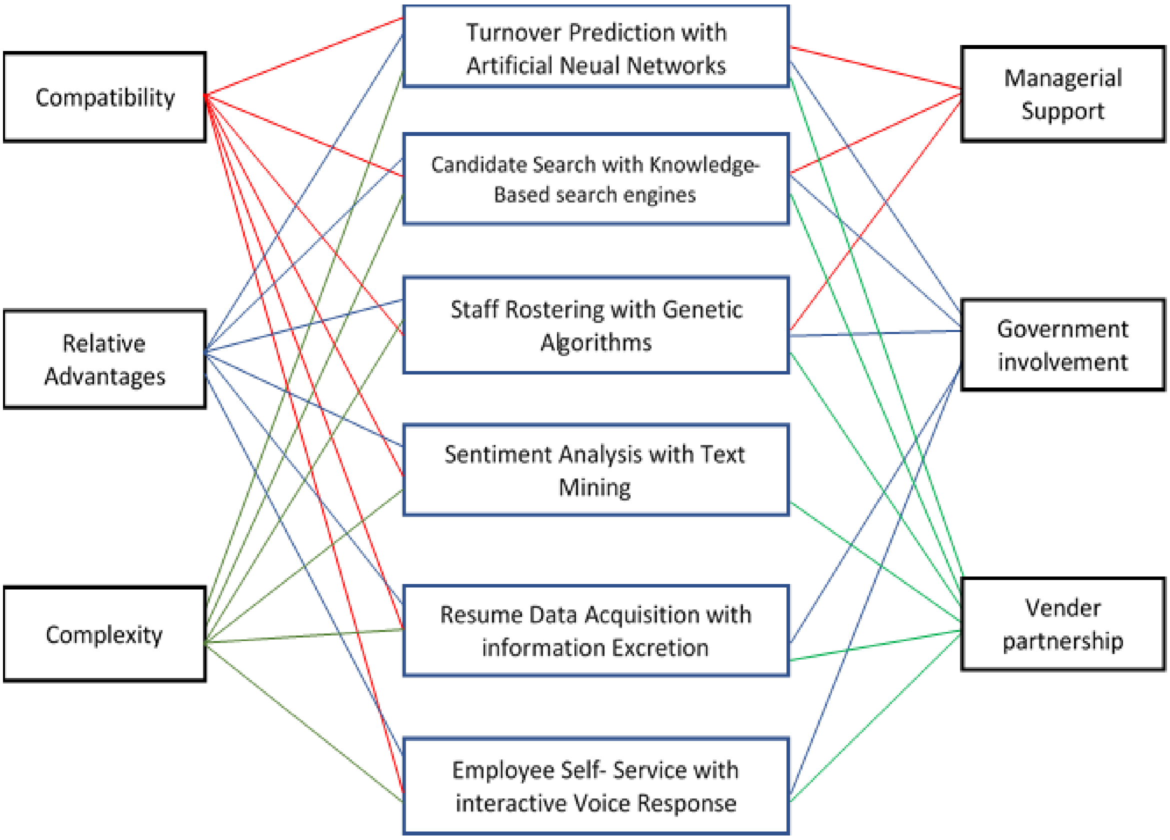
Particularly, the success factors that have been considered are compatibility, relative-advantage, complexity, managerial support, government involvement, and vendor partnership. While on the scenarios of AI in HRM side, they are turnover prediction with artificial neural networks, candidate search with 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 the 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



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. Third part is built the relationship 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.

Result analysis and Finding

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 et al., 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”. Moreover, Wamba et al. (2021) defined AI as “machines or computer systems capable of learning to perform tasks that normally require human intelligence”.

To understand AI scientifically, we should analyse the building blocks that AI’s constitute. According to Boisseau and 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 a study released by PWC Global artificial intelligence in 2017 (PwC, 2017), AI will impact the GDP of countries by 2030 as the following. China 26.1%, North America 14.5%, Europe 11.5%, Asian markets 10.4%; which means 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. These applications are covering different tasks, including recruiting, selection, performance assessment and performance management (EY, 2020). For instance, Natural Language Processing (NLP) that develops human-like response and personalized expressions called chatbots (Kocaleva et al., 2016). A chatbot is one application of NLP 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.

AI scenarios in HRM

Human resources are widely considered as one of the most valuable assets of any organization (Markoulli et al., 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 et al., 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 applications 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.

Turnover prediction with artificial neural networks

Artificial Neural Networks (ANNs) are information processing systems that link different information 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 of ANNs in HRM is the prediction of employee turnover (Strohmeier & Piazza, 2015). 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.

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, then used this recognition to organize search results that guide users to improve their queries interactively (Otegi et al., 2015). Therefore, their functionality is reducing time-consuming and also increasing knowledge representation related to inquiries.

An application of knowledge-based search-engines in HRM is focusing on 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. This technology would be able to automate parts of the recruiting and selection process by offering reasonable details on the potential candidates (Luger, 2005).

Staff rostering with genetic algorithms

Genetic algorithms are problem-solving techniques inspired by biological technology to identify the goodness of individuals (Shukla et al., 2015). Genetic algorithms generate solutions according to a specified objective function and problem specific constraints (van Esch et al., 2021).

An application 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 multiple criteria, such as costs, job-person fit and employee preferences.

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 et al., 2015). Title detection 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. For instance, identifying opinions and sentiments on a specific issue such as employee satisfaction, compensation ratios, career possibilities and quality of training would support decision-makers in planning for the next HRM activities (Akilan, 2015).

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 et al., 2018).

An application scenario of IE in HRM is résumé data acquisition (Strohmeier & Piazza, 2015). Through the recruitment process, the HR department revises a number of résumés in text documents format. These documents are usually analyzed by individuals, in order to extract information from job applicants. 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).

Employee self-service with interactive voice response

Interactive voice response (IVR) works on increasing interaction between human and computers via voice (Howell et al., 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 transferring 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 (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 et al., 2019).

Overall, specific scenarios have proofed the relevance of AI applications in HRM. They open the door for organizations to take advantages of AI in improving outcomes on specific HRM tasks (Finlay, 2017). At this point, the question now is which are the successful adopting factors in order to leverage the advantages of AI in HRM (Lengnick-Hall et al., 2018). The next section seeks to answer the second question.

Adopting factors of AI in HRM scenarios

AI can create enormous benefits for organizations, but it can also bring risks and adverse impacts into a passive situation if the organizations are unable to design a full framework in order to adopt factors of AI successfully (Wanner et al., 2020). Success factors are necessary to successful AI implementation. These factors play a key role in improving the quality of decision-making. This study is introducing multiple success factors introduced by Chen (2019), which are compatibility, relative advantage, complexity, managerial support, government involvement, and vendor partnership.

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 (Chong & Olesen, 2017). Previous literature considers that compatibility has a positive influence both, on IT adoption in general, and on AI in particular (Gangwar et al., 2015; Verma & Chaurasia, 2019). 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 (Binsawad et al., 2019; Mahesh et al., 2018).

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 et al., 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 influencing attitudes towards AI adoption (Awiagah & Lim, 2015). Furthermore, managerial support is necessary in order to encourage the 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 et al. (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, 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 et al., 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).

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 process.

The result of the analysis shows that the AI applications are affected directly on the HRM functions.

The adoption factors of AI in HRM 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. Future research could further study 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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Are we ready to implement artificial intelligence in HR performance management?

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Abstract

The fast pace of innovation and disruption in business processes and technology today requires employees to be continuously up-skilled and be able to adapt to changing practices depending on the emerged technology. The purpose of this paper is to explore whether artificial intelligence is fully implemented in all processes of HR performance management (HRPM) through thematic analysis for the respondents of eight interviewees on Open-ended questions. The result reveals that AI implementation on the full process of HRPM is relatively limited. The thoughts in the paper distinction between the recent use of AI in the HRPM process far away from expectation and desired.

Introduction

The willingness of the organization to rebuild the internal business environment taking into account the latest digitalization trends is considered a key factor in the competitive market (Qi & Yao, 2021). Artificial intelligence (AI) is one of the main components of current digitalization trends. It has attracted more attention from researchers, practitioners and technical developers to figure out the strengthening human-machine interactions and fostering automation through integrations between business demand and intelligent software (Pereira et al., 2021). AI is aimed at making machines think like humans but surpassing the way humans work. Depending on autonomously gathering and processing data from several inputs to make decisions, solve problems and undertake other actions to improve task execution and performance.

HR Performance Management (HRPM) has a significant contributing factor to organizational success and the improvement of employees' performance. Integrating the processes of HRPM along with AI can generate substantial benefits for organizations (Garg S. et al., 2021).

Performance Management (PM) activities have been recognized as the cornerstone of human resource management (HRM) by aligning employee management to organizations' overall objectives (Tweedie et al., 2019). The concept implies arranging activities in order to improve, manage and measure the performance of individuals or teams, paying close attention to organization effectiveness (Becker et al., 2011). These activities are revolved around performance planning, managing performance, performance reviews and performance assessment (Armstrong & Taylor, 2020). Each one of these activities are encompassed different components. Performance planning refers to strategic objectives, key performance indicators and performance targets, while performance assessment refers to the review and feedback of PM components to determine the scope of growth in an employee's career path (Broadbent & Laughlin, 2009). Therefore, the overall goal of PM is to maintain the objectives of the organization and its stakeholders through aligning activities in an optimum fashion to achieve the desired goals (Gruman & Saks, 2011).

HRPM systems have been affected by the rapid development in technology advancement, Internet and Information Technology (IT) revolution (Giri et al., 2019). This revolution has a strong influence on HRM and practices and is moving them in a completely new direction (Priya & Sinha, 2019). The most advanced revolution that is poised to unleash the next wave of digital transformation in HRPM is AI (Pillai & Sivathanu, 2020). AI technology is bringing in new functionalities to HRM and changing the way human resources are managed in an organization (Erro-Garces, 2021; Pillai & Sivathanu, 2020). These functionalities stretched the geographical boundaries of HRM practices, offer employees new ways of working by eliminating physical and time barriers relying on HRM shared services such as virtual workplace and virtual teams (Bondarouk & Brewster, 2016). Therefore, AI has been gradually applied to enterprise management decision making, taking on and helping managers to speed up their tedious and repetitive daily work. It provides powerful database and analytical support, enabling managers to shift away from routine tasks (Al-Harazneh & Sila, 2021).

Powerful database and analytical data mining are considered a reference point in PM technologies through collecting data from multiple sites within the organization on how an employee performs his job (Dhir & Chhabra, 2019). By linking these available data; line managers could come up with appropriate and objective proposals that predict and improve individual performance and help the organization to make positive decisions regarding employee's attitudes (Alrashedi & Abbod, 2020; Khan et al., 2021; Malik et al., 2021). For instance, AI could cluster employees into distinct groups based on their performance level and work satisfaction level (Chiu et al., 2021). Later, suitable strategies could be developed to improve the performance of underperformers and enhance the morale of dissatisfied employees. Moreover, an AI algorithm could be utilized to predict employees' performance level based on their background data and performance characteristics (Mikalef & Gupta, 2021). As a result, HRPM has witnessed significant changes in the way it has been managed due to the adoption of AI (Jarrahi, 2018).

In recent years, a new literature strand has begun to emerge, looking into the current adoption level of AI in HRPM within organizations (Zhang et al., 2021). Although research work on the implementation of AI in HRPM is emerging and increasingly growing. The full implementation of AI in the HRPM process; namely: performance planning, managing performance, performance reviews and performance assessment (Armstrong & Taylor, 2020), has not been studied in depth before. According to Wall and Schellmann (2021), authors of "We tested AI tools. Here's what we found", AI failed in recognizing answers for the same questions in different languages. Furthermore, failed in scoring candidates on the content of interviewees answers; the algorithm pulled personality traits from the interviewer's voice. Therefore, some researchers recommended expanding future research on PM and AI. For instance, Zhang et al. (2021) argue that future HRM research could benefit from applying big data at a micro level, employee attitude by applying big data collection techniques. At the macro level, HRM research can benefit from conducting people analytics, analyzing the implication of AI in assessing performance planning and cross-country HRM comparative research.

Improving clarity on the what is the reality of AI in HRPM and what is desiderate is essential for human-machine interactions. At the same time mapping and predicting the potential of this technology in order to foster automation is a key factor for future AI implementation across different levels of HRPM. Drawing on the above needs and gaps, the present study is set to answer the following research question:

RQ: What is the adoption level of AI in the HRPM process in companies?

Our analysis contributes to the HRM literature, and especially research in AI and PM in several ways. First, we explore the real adoption of AI in performance planning, managing performance, performance reviews and performance assessment. Second, how generated data could facilitate the role of HR managers.

The article is organized as follows. We first provide a literature review. Then we discuss the methods. Next, we analyze AI's potential in employee performance management. It is followed by a section of conclusion, practical implementation and limitations.

Literature Review

In a technology-driven business environment, technology is employed in various HR activities to maximize resource utilization and improve organizational performance. Recently, AI technology is one of these technologies that extensively used by the organization in recruiting (Ore & Sposato, 2021), selection (Borges et al., 2021), onboarding (Makarius et al., 2020) and intelligent personal assistant (Han & Yang, 2018). Leveraging big data analytics and self-learning capabilities, AI applications could provide a competitive advantage to the organization as it securitizes the data and offers solutions to improve PM. Through developing employees engaging, mapping talent, managing employee performance, measuring training impact, talent mobility management, prediction for hiring, retention and attrition of employees, planning employee welfare, outlining organization benefits and employee sentiment analysis (Sivathanu & Pillai, 2020).

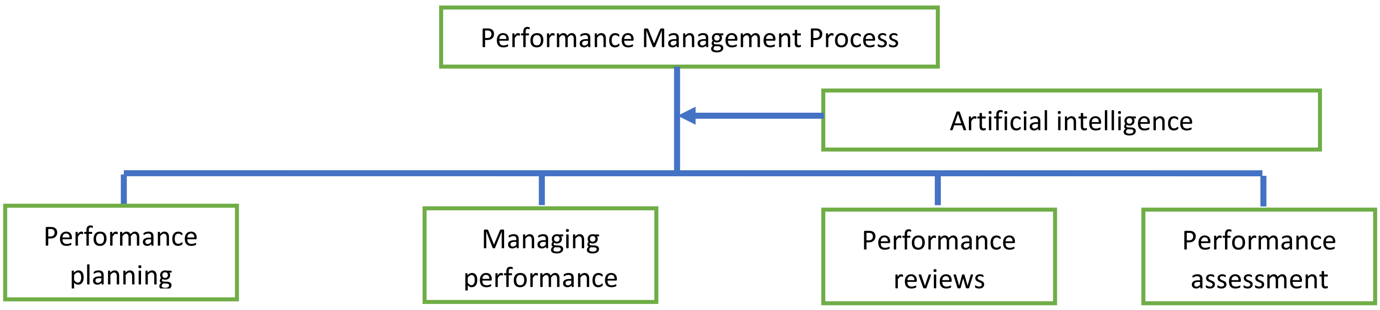
Evidence of the advanced role of AI in HRPM is demonstrated in redefined the learning and development strategies in the HR department to equip employees with essential information and skills, as well as improving their capacities to do difficult and dynamic tasks. This integration could be summarized through, first, analysing an employee's performance based on pre-defined performance parameters. Second, Identify training gaps by mapping performance ratings and trainee attributes to relevant KSAs. Third, identify the learner's preferred method and style of learning, including interpretation of trainee characteristics. Forth, choose the training program's duration, frequency, speed (tailored) and mode of delivery for the training program. Fifth, measure the trainee's personal development (relevant to the KSAs) using relevant parameters. Finally, schedule training programs in a calendar year to ensure maximum participation from the target audience, becoming linked with various training programs (Maity, 2019).

As a result of the potential integration of AI in HRPM, the time spent reviewing surveys distributed to discover individual characteristics is reduced; selecting the right set of learners for training programs; choosing the right training provider/trainer based on learner preferences; making training programs more interactive and management of organizational knowledge resources (Upadhyay & Khandelwal, 2019).

Drawing on the abovementioned advantages of AI technologies on HRPM. Tong et al. (2021) argue that implementing AI in HRPM will improve the performance of employees for two reasons. First, AI is able to rapidly analyze a large amount of data on employees' activities and behaviour, thereby boosting the accuracy of performance appraisals. Accurate information on how much and how well employees work has always been seen by business management as a crucial road to increased job productivity (Tomczak et al., 2018). Second, AI can generate recommendations that are more relevant for each employee on jobs with well-structured tasks. The power of AI analytics to quickly analyze massive amounts of data enables it to provide "personalized" advice at scale, that is, to make accurate and personalised recommendations (Dhir & Chhabra, 2019).

However, the development of employees performance reflects on financial performance, organizational effectiveness, customer satisfaction, operational effectiveness and other outcomes. Literature has been emphasized on AI in PM generally, while the depth analysis of AI implementation in each part of HRPM (See figure 1) is sparse. This research will help to cover this gap, by exploring the practical implementation of AI from a practitioners point of view.

Figure 1: artificial intelligence implementation in HRPM process



Methodology

Semi-structured interviews, commonly used in a qualitative descriptive research approach, as the data collection instrument (Bluhm et al., 2011; Saunders et al., 2016). The semi-structured interviews were conducted by the researcher using ZOOM software for eight professionals with an average work experience of 12.4 years and working across seven countries (See table1). These professionals were identified using the LinkedIn network based on their practical experiences at AI in HRM and the interviewees were asked about the implementation of AI in performance planning. Reviews, assessment and managing performance.

Table 1: Interviewee data

Num.	Title / Position	Years of experience	Interview duration
1	Sr. artificial intelligence and SAP consultant	16	30 minutes
2	Co-founder of AI platform company	14	28 minutes
3	Senior artificial intelligence developer	13	51 minutes
4	HR & Talent Tech start-up, AI consultant	15	41 minutes
5	SAP Success Factors Consultant	11	38 minutes
6	Director solutions consulting at oracle	16	43 minutes
7	Hiring solutions selling for AI	10	32 minutes
8	Director and AI consultant at PWC	16	31 minutes

With consent from the participants, the semi-structured interviews were recorded and transcribed verbatim to avoid distortion of the participants' views. Transcription accuracy was enhanced by reading the transcription and comparing it with the audio recording. Any inaccuracy that was discovered was promptly addressed. Thematic analysis is adopted instead of other data analysis approaches, because it provides the researcher with an opportunity to stay close to the data, with minimal transformation during analysis (Braun & Clarke, 2006). A data analysis process was followed of listening to audio recordings, transcribing, reading and re-reading the transcriptions and importing them into ATLAS. ti qualitative data analysis software. The researcher used both open coding and in vivo coding to maintain the participants' views. The codes were reviewed by renaming, merging and splitting, where necessary, until patterns in the data could be identified. The relationship between codes was established by using the function of project explorer and networks in ATLAS.ti (Paulus & Lester, 2016).

Additional codes were generated and further analysed to determine the emergent themes. The data codes were then sorted into potential themes related to the research question. Themes were extracted from the data sets to represent a true or superficial view as a realistic interpretation of the participants' perspectives. The information was anonymised and the respondents have been addressed as R1, R2, R3, R4, R5, R6, R7 and R8 in the further discussions.

Findings

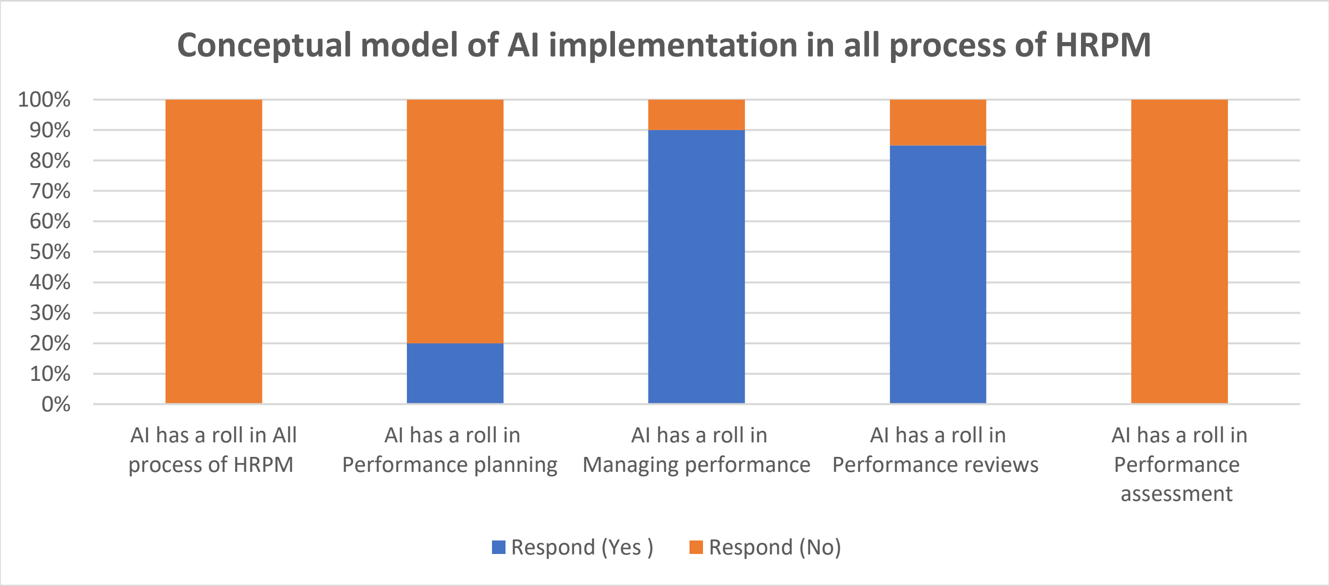
This qualitative study is focused on the subjective experience of AI consultants and data analysis in HR applications. The participants shared their views and experiences about the various AI implementation in HRPM within their organizations. Following are the findings from the interviews with the respondents (See figure 2), the themes and subthemes that emerged out of the analysis run on the data collected.

Existence of AI in HRPM

There is no doubt within respondents on the general advance roll of AI in PM, through offering for organizations dynamic platforms to share their practices and knowledge resources with their employees. However, all of them had agreed that AI is still far away from managing the full cycle of the HRPM process. Quoted below are some instances from the respondent's answers:

> *R4: " There are some initiatives from leveraging AI in portions of performance management cycle, but still is not mature enough."*
>
> *R5: "AI in performance management is still in early-stage because AI faced difficulties in recognizing the difference between tangible and intangible skills."*
>
> *R7: "AI being an independent system to handle performance management cycle, is still far away from what we are expecting."*

Figure 2: Conceptual model of AI implementation in All processes of HRPM



The recent use of AI in the HRPM process

However, the development of AI in collecting massive amounts of data, analysing data and generating actionable insights for a relevant challenge in developing employee performance. There is a severe limitation in some areas of the HRPM process:

AI in performance planning: 80 percent of respondents believed that the AI algorithm is unable to extract the required knowledge, skills and behavioural competencies needed to perform the job from the job description. Quoted below are some instances from the respondent's answers:

> *R1: "I often found difficulties for AI to identify the competencies needed from employees as well as KSA required."*

> *R8: We still have a debate on the role of AI in planning the desired competencies needed from employees. AI is unable to extract correct KSA from job description".*

AI in managing performance: 90 percent of respondents believed that AI is able to manage practices of setting direction, monitoring, and assisting performance and making recommendations accordingly.

> *R7: "AI is solving a lot of problems in terms of looking forward to what needs to be done by an employee to achieve the purpose of their job; to meet new challenges; to make even better use of their knowledge, skills and abilities and to develop their capabilities."*

> *R2: "One of the major advances of AI is crystallized in recommending advice to improve employee attitude based on deep data analysis."*

AI in performance review: 80 percent of respondents believed that AI demonstrated an advanced role in reviewing employees' annual performance and customized feedback based on their annual attitude.

> *R3: "For example, you conducting a first orientation for an employee based on the job description and KPI. Then AI can follow the annual progress and achievement of this employee to reach the desired goal. If not achieved, AI will offer feedback and recommendations".*

AI in performance assessment: 100 percent of respondents were unsure of the quality of AI applications in overall assessment and rating, leading to promotion or judgment.

> R6: "If a junior employee is evaluated by AI to be a senior. How could AI manage intangible skills? Or, are we sure from evaluation components created by AI. I think AI hasn't a role in performance assessment".

Conclusion, Practical Implementation and Limitations

Combining the four processes of PM, various applications of AI in HRPM, thematic analysis of semi-structured and building on the work of (Hamilton & Sodeman, 2020), a conceptual model of AI implementation in All processes of HRPM has emerged. This framework rests on five pillars, AI implementation in the HRPM process, AI in performance planning, AI in managing performance, AI in performance review and AI in performance assessment.

The study reveals that the implementation of AI on the full process of HRPM is relatively limited if we compare it with other tasks such as recruitment and selection. This conclusion is similar to the argument of Garg s et al. (2021) that AI is more advanced in recruitment if we compare it to other HR functions. In detail, AI has clear applications in managing performance, setting direction, monitoring, performance review and customized feedback. In contrast, AI and algorithms have limitations in performance planning, extracting the required knowledge, skills and ability, performance assessment and judgment.

Building on this piece of research, new lines for future research could be opened, such as the barriers to implementing AI in performance planning and assessment. However, AI has the ability to deal with massive datasets and conduct deep learning to analyse structured and unstructured data. Furthermore, the researcher could apply quantitive research methodology to figure out the competencies required to adopt AI in performance planning and assessment to facilitate the job of data scientists and AI developers.

Regarding to practical implications, this paper sets the foundations for HR Analytics; Workforce Intelligence Officer; Head of HR Digital transformation and data analysis to identify the weakness and strength of AI in the HRPM process in order to cover this gap.

This research makes a novel contribution to promoting awareness among researchers and AI developers on the adverse impact of generalizing the advanced role of AI in all areas of HRPM. It helps to develop a distinction between the recent use of AI in the HRPM process far away from expectation and desired.

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The role of artificial intelligence in transforming HRM functions. A literature review

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Abstract

Artificial intelligence (AI) has revolutionized the way employees and managers work. This paper investigates how literature analysis AI transforming in Human Resource Management (HRM) functions: staffing, learning & development and motivation. Using recent advances in science mapping, this article analyses 30 journals and proceedings using three main keywords: “Artificial intelligence”; “Human Resource Management”; and “Transformation”. All the consulted papers have been published in Scopus databases between 1998 to 2021 in order to explore and understand topic content and intellectual structure of how AI is transforming HRM functions. The results reveal a gap in literature to build a complete framework for the transforming role of AI in HRM functions. Particularly in strategic HR planning, job design and compensation. This study gives insights and foundations for researchers to expand their study on the role of AI in HRM.

Purpose of the paper

Artificial intelligence (AI) offers advantages that may transform practices of HRM (Ore & Sposato, 2021), and the way people is managed (Xiong et al., 2020). Despite, there are several studies on the applications of AI on HR functions, such as the use of AI in recruitment (Dennis, 2018; Upadhyay & Khandelwal, 2018), or how AI is applied in performance management (Buck & Morrow, 2018; Zehir et al., 2020), there is still a noticeable gap in the in-depth analyzing of the transforming role of AI in the overall HRM functions. Taking this into account, this piece of paper sheds light on understanding the value added by adopting AI in HRM functions. Therefore, the main goal is, on the one hand, to identify the significant role of AI in transferring HRM functions. On the other hand, improve the conceptual knowledge of HR scholars and practitioners on the recent digital transformation in HRM process.

Related Work

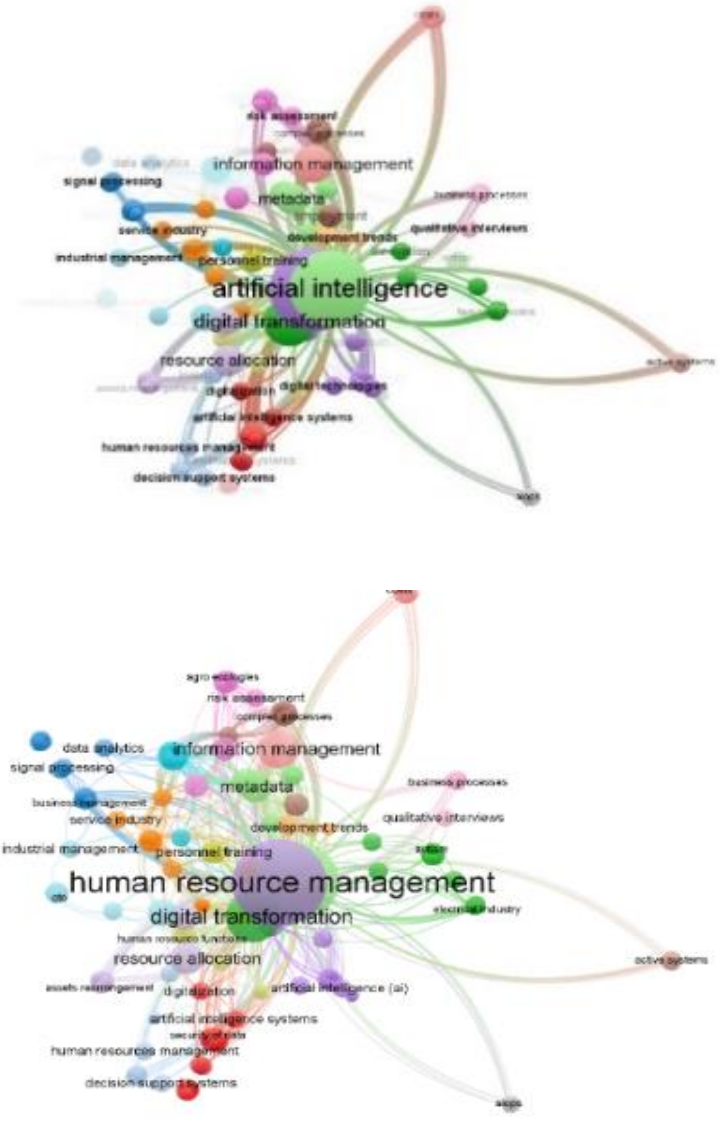
According to a digital HR Survey conducted in 2020 by PWC covering 608 executives and HR professionals, 55% of respondents believe HR’s most significant contribution to digital transformation is digitalizing HR processes (PWC, 2020). Along a similar line, Mercer's Global Talent Trends 2019 reported that 60% of companies plan to boost their use of automated workplaces by 2020, including 59% in the United States and 55% in China (Mercer, 2019). This explains why organizations worldwide are increasing their HR investments in AI and related technology, trying to catch up with AI’s transformational role in HRM functions. Several scholars studied and proposed models that have linked the role of AI and HRM functions.

Pillai and Sivathanu (2020), investigate the transforming role of AI technology when adopted on talent acquisition. They provide vital insights for HR managers to benchmark AI’s activities required in talent acquisition. Similarly, Tahira (2021) addresses the possibilities of AI in transforming and supporting HRM functions like recruitment, training, talent management and retention through analyzing secondary research data. Moreover, Geetha R and Bhanu (2018) study how AI influences the recruitment process by highlighting AI's adoption techniques in recruitment based on secondary sources of information. In the same way, Zel and Kongar (2020) emphasize the growing role of AI in HR functions to design an enhanced digital employee experience.

Design/Methodology/Approach

The methodology used in this paper is a literature review (LR) to analysis topic content and intellectual structure between 1998 to 2021. LR employs a specific methodology of collecting and analyzing data from the existing literature (Mackenzie et al., 2012), by associating data to conclusions in order to clarify what is known and unknown (Tranfield et al., 2003). Data source was the Scopus database, generated from three keywords extracted from VOSviewer software ("Artificial intelligence"; "Human Resources Management"; "Transformation"), (See Figure1).

Figure 1: Images of the VOSviewer Network Visualization of the AI ,HRM and Transformation Maps



The keywords search has been selected without any filter such as “SU - Subject Terms” or period, in English language, from academic and scientific journals and materials presented at conferences.

Findings

As a result of the research, 30 publications were found. Of the total, 8 of them (weight 26.7%) are articles and 22 conference papers (weight 73.3%). Noteworthy that most studies (95.3%) were published between 2017 and 2021.

In detail, in 2020 there is a sudden increase in interest in the topic. This "Growth Period" is verified by the number of publications (15 out of 30), which represented 50% of the total research. It is also essential to understand how transformation and the advancement of AI has influenced this shift in the landscape of interest in HR research. Specifically, in the last three years (2019, 2020 and 2021), 77.4% of the articles were explicitly focused on recruitment & selection, onboarding and performance management. For example, Malini and Srinivas (2020) describe the transformation role of AI on various HRM functions like recruitment, onboarding, learning and development, Performance management, social sharing and compensation. The rest publications (represented 22.6%) are related to the advancement of AI in minimizing the administrative work of HR to take up with the strategic role. Tewari and Pant (2020) reinforce the understanding of how AI is enabling machines to make decisions more accurately than humans based on existing data sets and behavioral patterns. This transformation pushes machines to take over all work susceptible to be automatized leading HR professionals to take up more strategic and intellectual roles.

In terms of the area of knowledge where the papers are published, it is worth highlighting that business, management, and accounting subjects are covered by only 12.7% from the whole subject areas in the Scopus database.

In this sample, the transforming role of AI in HRM functions is distributed with different objectives in the area of HR. These areas are work-related flexibility, creativity and innovation, AI-enabled in HRM systems, employee emotions wellbeing at AI-powered workplace, recruiting and selecting, Internet of Things (IoT) and Machine learning (ML), performance management and learning and development.

In conclusion, it could be said that daily advances of AI constitute, on the one hand, a new approach in managing employees and enhancing firm performance. On the other hand, considerable challenges are still addressed when adopting AI in HRM.

Finally, the literature fails to build a complete framework for the transforming role of AI in HRM functions. Particularly, strategic HR Planning and staffing, job design, motivation and compensation.

Research limitations/implications

The scope of databases is limited to Scopus. However, due to the scarcity of papers found, this analysis could be expanded to other databases to cover ISI, Emerald insight and Google Scholar.

Building on this piece of research, new lines for future research could be opened, such as building a comprehensive framework based on qualitative or quantitative analysis covering staffing, motivation, and learning and development in order to deepen understanding of the transforming role of AI in HRM functions.

Practical implications

The papers and proceedings analyzed in the present study show variations in the interest in researching the theme, methods and applications of AI on HRM functions. As far as academic implications concern, this study highlights the need for empirically expanding the analysis of the role of AI in HRM.

Regarding practical implications, this paper sets the foundations for practitioners to efficiently plan the implementation of AI in HRM in order to get the most out of it.

Originality/Value of the paper

This article advances research on the transforming role of AI in HRM functions by analyzing topics content and intellectual structure of business and management scholarship.

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AI definition in HRM derives from (Article #1 (4.1)):

AI definitions

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AI in HRM can be seen as a technology that consists of machine learning and deep learning, capable of mimicking human cognitive activities to achieve HRM practices

Elsevier results (Article #1 (4.1))

Human Resource :
70 document results TITLE-ABS-KEY (" **Human Resource** " , " **Artificial intelligence** ") AND DOCTYPE (ar) AND PUBYEAR > 2009 AND (LIMIT-TO (SUBJAREA , "BUSI") OR LIMIT-TO (SUBJAREA , "SOCI")) AND (LIMIT-TO (LANGUAGE , "English"))
2 document results TITLE-ABS-KEY (" **Human Resource** " , " **Artificial intelligence application** ") AND DOCTYPE (ar) AND PUBYEAR > 2009
27 document results TITLE-ABS-KEY (" **Human Resource** " , " **natural language processing** ") AND DOCTYPE (ar) AND PUBYEAR > 2009
31 document results TITLE-ABS-KEY (" **Human Resource** " , " **Text mining** ") AND DOCTYPE (ar) AND PUBYEAR > 2009
35 document results TITLE-ABS-KEY (" **Human Resource** " , " **Expert system** ") AND DOCTYPE (ar) AND PUBYEAR > 2009
21 document results TITLE-ABS-KEY (" **Human Resource** " " **Robotics** ") AND DOCTYPE (ar) AND PUBYEAR > 2009 AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (SUBJAREA , "SOCI") OR LIMIT-TO (SUBJAREA , "BUSI"))
5 document results TITLE-ABS-KEY ("**Human Resource** " , " **Machine vision** ") AND DOCTYPE (ar) AND PUBYEAR > 2009
2 document results TITLE-ABS-KEY ("**Human Resource** " , " **chatbots** ") AND DOCTYPE (ar) AND PUBYEAR > 2009
32 document results TITLE-ABS-KEY ("**Human Resource** " , " **Machine Learning** ") AND DOCTYPE (ar) AND PUBYEAR > 2009 AND (LIMIT-TO (SUBJAREA , "BUSI") OR LIMIT-TO (SUBJAREA , "SOCI"))
36 document results TITLE-ABS-KEY ("**Human Resource** " , " **Deep learning** ") AND DOCTYPE (ar) AND PUBYEAR > 2009
33 document results TITLE-ABS-KEY ("**Human Resource** " , " **neural network** ") AND DOCTYPE (ar) AND PUBYEAR > 2009 AND (LIMIT-TO (SUBJAREA , "BUSI") OR LIMIT-TO (SUBJAREA , "SOCI"))
14 document results TITLE-ABS-KEY ("**Human Resource** " , " **Predictive analytics** ") AND DOCTYPE (ar) AND PUBYEAR > 2009
53 document results TITLE-ABS-KEY ("**Human Resource** " " **Data Mining** ") AND DOCTYPE (ar) AND PUBYEAR > 2009 AND (LIMIT-TO (SUBJAREA , "SOCI") OR LIMIT-TO (SUBJAREA , "BUSI"))
63 document results TITLE-ABS-KEY (" **Human Resource** " , " **Big data** ") AND DOCTYPE (ar) AND PUBYEAR > 2009 AND (LIMIT-TO (SUBJAREA , "BUSI") OR LIMIT-TO (SUBJAREA , "SOCI"))

Artificial intelligence
25 document results TITLE-ABS-KEY (" **Artificial intelligence** " , " **Recruiting** ") AND DOCTYPE (ar) AND PUBYEAR > 2009
9 document results TITLE-ABS-KEY **(** " **Artificial intelligence** " , " **Performance appraisal** ") AND DOCTYPE (ar) AND PUBYEAR > 2009
56 document results (TITLE-ABS-KEY (" **Artificial intelligence** " , " **Selection** ") AND DOCTYPE (ar) AND PUBYEAR > 2009) AND (human AND resource) AND (LIMIT-TO (SUBJAREA , "BUSI") OR LIMIT-TO (SUBJAREA , "SOCI")) AND (LIMIT-TO (LANGUAGE , "English"))
2 document results TITLE-ABS-KEY (" **Artificial intelligence** " , " **Job posting** ") AND DOCTYPE (ar) AND PUBYEAR > 2009
2 document results TITLE-ABS-KEY (" **Artificial intelligence** " , "**Professional career** ") AND DOCTYPE (ar) AND PUBYEAR > 2009
32 document results TITLE-ABS-KEY (" **Artificial intelligence** " "**Promotion** ") AND DOCTYPE (ar) AND PUBYEAR > 2009 AND (LIMIT-TO (SUBJAREA , "SOCI") OR LIMIT-TO (SUBJAREA , "BUSI"))
8 document results TITLE-ABS-KEY (" **Artificial intelligence** " , "**career development** ") AND DOCTYPE (ar) AND PUBYEAR > 2009
1 document result TITLE-ABS-KEY (" **Artificial intelligence** " , " **performance review** ") AND DOCTYPE (ar) AND PUBYEAR > 2009.

Final list of articles analysed (Article #1 (4.1))

Selected Articles	Authors	Journal	Developing AI definition in HRM / AI applications in HRM	Research type: Quantitative /Qualitative	Year of publishing
1. Recruitment in the Times of Machine Learning	Rab-Kettler, Karolina Lehnervp, Bada	Management Systems in Production Engineering	AI applications in HRM	Conceptual approach	2019
2. Embracing AI and Big Data in customer journey mapping: From literature review to a theoretical framework	Arco, Mario D. Presti, Letizia Lo Marino, Vittoria Resciniti, Riccardo	Innovative Marketing	Developing AI definition in HRM	Conceptual approach	2019
3. Using natural and artificial intelligence in the talent management system	Vinichenko, Mikhail V. Rybakova, Marina V. Chulanova, Oxana L. Kuznetsova, Irina V. Makushkin, Sergey A. Lobacheva, Anastasia S.	International Journal of Recent Technology and Engineering	Developing AI definition in HRM	Qualitative approach	2019
4. Task recommender system using semantic clustering to identify the right personnel	Bafna, Prafulla Shirwaikar, Shailaja Pramod, Dhanya	VINE Journal of Information and Knowledge Management Systems	AI applications in HRM	Quantitative approach	2019
5. Leverage big data analytics for dynamic informed decisions with advanced case management	Osuszek, Lukasz Stanek, Stanislaw Twardowski, Zbigniew	Journal of Decision Systems	Developing AI definition in HRM	Qualitative approach	2016
6. AI-enabled recruiting: What is it and how should a manager use it?	Black, J. Stewart Esch, Patrick	Business Horizons	Developing AI definition in HRM	Conceptual approach	2020
7. The mirror for (artificial) intelligence in capitalism	Moore, Phoebe V.	Capital and Class	Developing AI definition in HRM	Qualitative approach	2020
8. Artificial Intelligence in Service	Huang, Ming Hui Rust, Roland T.	Journal of Service Research	Developing AI definition in HRM	Qualitative approach	2018
9. How Artificial Intelligence affords digital innovation: A cross-case analysis of Scandinavian companies	Cristina Trocin Ingrid Våge Hovland Patrick Mikalef Christian Dremel	Technological Forecasting and Social Change	AI applications in HRM	Qualitative approach	2021
10. Feature Regularization and Deep Learning for Human Resource Recommendation	Wang, Haoxiang Liang, Guihuang Zhang, Xingming	IEEE Access	AI applications in HRM	Quantitative approach	2018
11. The challenges of AI and blockchain on HR recruiting practices	Michailidis, Maria P.	Cyprus Review	AI applications in HRM	Conceptual approach	2018

12. How will service robots redefine leadership in hotel management? A Delphi approach	Xu, Shi Stienmetz, Jason Ashton, Mark	International Journal of Contemporary Hospitality Management	AI applications in HRM	Qualitative approach	2020
13. Gear classification for defect detection in vision inspection system using deep convolutional neural networks	Kamal, I.M. Sutrisnowati, R.A. Bae, H. Lim, T.	ICIC Express Letters, Part B: Applications	AI applications in HRM	Quantitative approach	2018
14. Data Mining in Nonprofit Organizations, Government Agencies, and Other Institutions	Wang, Zhongxian Yan, Ruiliang Chen, Qiyang Xing, Ruben	International Journal of Information Systems in the Service Sector	Developing AI definition in HRM	Qualitative approach	2010
15. Algorithms, artificial intelligence and automated decisions concerning workers and the risks of discrimination: the necessary collective governance of data protection	Todolí-Signes, Adrián	Transfer	Developing AI definition in HRM	Qualitative approach	2019
16. Intelligent human resource information system (i-HRIS): A holistic decision support framework for HR excellence	Masum, Abdul Kadar Beh, Loo See Azad, Abul Kalam Hoque, Kazi	International Arab Journal of Information Technology	Developing AI definition in HRM	Qualitative approach	2018
17. Artificial intelligence in human resources management: Challenges and A path forward	Tambe, Prasanna Cappelli, Peter Yakubovich, Valery	California Management Review	Developing AI definition in HRM	Qualitative approach	2019
18. Big Data for Development: A Review of Promises and Challenges	Hilbert, Martin	Development Policy Review	Developing AI definition in HRM	Conceptual approach	2016
19. Artificial intelligence techniques in human resource management—A conceptual exploration	Strohmeier, S. Piazza, F.	Intelligent Systems Reference Library	AI applications in HRM	Conceptual approach	2015
20. Digital recruitment: The evolution of assessment by artificial intelligence	Lochner, Katharina Preuß, Achim	Gruppe. Interaktion. Organisation	AI applications in HRM	Qualitative approach	2018
21. A review paper on artificial intelligence at the service of human resources management	Siham Berhil1 Habib Benlahmar Nasser Labani	Indonesian Journal of Electrical Engineering and Computer Science	Developing AI definition in HRM	Conceptual approach	2020
22. Deep learning diffusion by infusion into preexisting technologies – Implications for users and society at large	Emma Engström Pontus Strimling	Technology in Society	Developing AI definition in HRM	Conceptual approach	2020
23. Method of optimizing the dimensional features in sentiment analysis	Murali Krishna, M. Lavanya Devi, G.	International Journal of Computers and Applications	AI applications in HRM	Quantitative approach	2019
24. Exploring the impact of artificial intelligence on teaching and learning in higher education	Popenici, Stefan A.D. Kerr, Sharon	Research and Practice in Technology	Developing AI definition in HRM	Conceptual approach	2017

		Enhanced Learning			
25. Factors that influence new generation candidates to engage with and complete digital, AI-enabled recruiting	Esch, P. Black, J.S.	Business Horizons	AI applications in HRM	Qualitative approach	2019
26. Transformation towards smart factory system: Examining new job profiles and competencies	Jerman, A. Pejić Bach, M. Aleksić, A.	Systems Research and Behavioral Science	Developing AI definition in HRM	Qualitative approach	2020
27. Mining the voice of employees: A text mining approach to identifying and analyzing job satisfaction factors from online employee reviews	Jung, Y. Suh, Y.	Decision Support Systems	AI applications in HRM	Qualitative approach	2019
28. Face Detection in Security Monitoring Based on Artificial Intelligence Video Retrieval Technology	Dong, Z. Wei, J. Chen, X. Zheng, P.	IEEE Access	AI applications in HRM	Quantitative approach	2020
29. Artificial intelligence for innovation in Austria	Prem, Erich	Technology Innovation Management Review	Developing AI definition in HRM	Qualitative approach	2019
30. Robotic automation of employee onboarding using neural computing	Biswal, S.S. Ganesh, A. Madhavan, P.	International Journal of Scientific and Technology Research	AI applications in HRM	Qualitative approach	2020
31. Artificial intelligence, machine learning and process automation: existing knowledge frontier and way forward for mining sector	Ali, D. Frimpong, S.	Artificial Intelligence Review	Developing AI definition in HRM	Conceptual approach	2020
32. Role of artificial intelligence while hiring through referral recruitment: A conceptual review and model for future research	Kundhavai, S. Sumathi, K. Inayath Ahamed, S.B.	International Journal of Psychosocial Rehabilitation	AI applications in HRM	Conceptual approach	2020
33. A fuzzy expert system (FES) tool for online personnel recruitments	Daramola, J.O. Oladipupo, O.O. Musa, A.G.	International Journal of Business Information Systems	AI applications in HRM	Qualitative approach	2010
34. How Far have we come with the study of artificial intelligence for recuritment process	Nawaz, Nishad	International Journal of Scientific and Technology Research	AI applications in HRM	Qualitative approach	2019
35. Beyond design and use: How scholars should study intelligent technologies	Bailey, Diane E. Barley, Stephen R.	Information and Organization	Developing AI definition in HRM	Qualitative approach	2019
36. Recruitment through artificial intelligence: A conceptual study	Geetha, R. Bhanu Sree Reddy, D.	International Journal of Mechanical Engineering and Technology	AI applications in HRM	Conceptual approach	2018
37. Neural network model for the prediction of safe work behavior in construction projects	Patel, D.A. Jha, K.N.	Journal of Construction Engineering and Management	AI applications in HRM	Qualitative approach	2015

38. SamBot - Intelligent conversational bot for interactive marketing with consumer-centric approach	Pradana, A. Sing, G.O. Kumar, Y.J.	International Journal of Computer Information Systems and Industrial Management Applications	AI applications in HRM	Qualitative approach	2017
39. Smart tourism empowered by artificial intelligence: The case of Lanzarote	Ferràs, X. Hitchen, E.L. Tarrats-Pons, E. Arimany-Serrat, N.	Journal of Cases on Information Technology	Developing AI definition in HRM	Qualitative approach	2020
40. Explicating the future of work: perspectives from India	Bhattacharyya, S.S. Nair, S.	Journal of Management Development	Developing AI definition in HRM	Qualitative approach	2019
41. Big data contributions to human resource management: a systematic review	Garcia-Arroyo, J. Osca, A.	International Journal of Human Resource Management	Developing AI definition in HRM	Qualitative approach	2019
42. Machine learning for enterprises: Applications, algorithm selection, and challenges	Lee, I. Shin, Y.J.	Business Horizons	Developing AI definition in HRM	Qualitative approach	2020
43. An HR perspective: The global hunt for talent in the digital age	Dickson, D.R. Nusair, K.	Worldwide Hospitality and Tourism Themes	AI applications in HRM	Qualitative approach	2010
44. When Robots Replace Human Managers: Introducing the Quantifiable Workplace	Sahota, N. Ashley, M.	IEEE Engineering Management Review	Developing AI definition in HRM	Qualitative approach	2019
45. Model employee appraisal system with artificial intelligence capabilities	Shanmugam, S. Garg, L.	Journal of Cases on Information Technology	AI applications in HRM	Qualitative approach	2015
46. Implementation of artificial intelligence system and traditional system: A comparative study	Kim, J.B.	Journal of System and Management Sciences	Developing AI definition in HRM	Qualitative approach	2019
47. AI-enabled biometrics in recruiting: Insights from marketers for managers	Esch, P. Stewart Black, J. Franklin, D. Harder, M.	Australasian Marketing Journal	AI applications in HRM	Qualitative approach	2020
48. Human capital and AI in industry 4.0. Convergence and divergence in social entrepreneurship in Russia	Popkova, Elena G. Sergi, Bruno S.	Journal of Intellectual Capital	Developing AI definition in HRM	Quantitative approach	2020
49. Text mining for human resources competencies: Taiwan example	Chung, C.-H. Chen, L.-J.	European Journal of Training and Development	AI applications in HRM	Qualitative approach	2019
50. From data to action: How marketers can leverage AI	Campbell, Colin Sands, Sean Ferraro, Carla Tsao, Hsiu Yuan (Jody) Mavrommatis, Alexis	Business Horizons	Developing AI definition in HRM	Conceptual approach	2020

51. Future of Work in the Digital World: Preparing for Instability and Opportunity	Lent, R.W.	Career Development Quarterly	AI applications in HRM	Conceptual approach	2018
52. The role of knowledge management infrastructure in enhancing job satisfaction: A developing country perspective	Masadeh, Raed Almajali, Dmaithan Abdelkarim Alrowwad, Alaaldin Obeidat, Bader	Interdisciplinary Journal of Information, Knowledge, and Management	Developing AI definition in HRM	Qualitative approach	2019
53. Industry 4.0 and the need for talent: a multiple case study of Taiwan's companies	Chang, Y.-H. Yeh, Y.-J.Y.	International Journal of Product Development	Developing AI definition in HRM	Qualitative approach	2018
54. Evaluating influence of artificial intelligence on human resource management using PLS-SEM (Partial least squares-structural equation modeling)	Chakraborty, S. Giri, A. Aich, A. Biswas, S.	International Journal of Scientific and Technology Research	AI applications in HRM	Qualitative approach	2020
55. Trends and opportunities of artificial intelligence in human resource management: Aspirations for public sector in Bahrain	Abdeldayem, Marwan Mohamed Aldulaimi, Saeed Hameed	International Journal of Scientific and Technology Research	Developing AI definition in HRM	Conceptual approach	2020
56. Patent document clustering with deep embeddings	Kim, J. Yoon, J. Park, E. Choi, S.	Scientometrics	Developing AI definition in HRM	Quantitative approach	2020
57. Robotic process automation: Strategic transformation lever for global business services?	Willcocks, L. Lacity, M. Craig, A.	Journal of Information Technology Teaching Cases	AI applications in HRM	Conceptual approach	2017
58. Vision based algorithm for people counting using deep learning	Padmashini, M. Manjusha, R. Parameswaran, L.	International Journal of Engineering and Technology(UAE)	AI applications in HRM	Quantitative approach	2018
59. Impact of disruptive technology on human resource management practices	Stanley, D.S. Aggarwal, V.	International Journal of Business Continuity and Risk Management	AI applications in HRM	Qualitative approach	2019
60. Intelligent video interview agent used to predict communication skill and perceived personality traits	Suen, H.-Y. Hung, K.-E. Lin, C.-L.	Human-centric Computing and Information Sciences	AI applications in HRM	Quantitative approach	2020
61. Big data and human resource management research: An integrative review and new directions for future research	Yucheng Zhang Shan Xu Long Zhang Mengxi Yang	Journal of Business Research	Developing AI definition in HRM	Conceptual approach	2021
62. Text mining approach to predict hospital admissions using early medical records from the emergency department	Lucini, F.R. S. Fogliatto, F.	International Journal of	AI applications in HRM	Qualitative approach	2017

	C. da Silveira, G.J. L. Neyeloff, J. Anzanello, M.J. de S. Kuchenbecker, R. D. Schaan, B.	Medical Informatics			
63. An artificial intelligence approach towards investigating corporate bankruptcy	Gherghina, Ș.C.	Review of European Studies	Developing AI definition in HRM	Qualitative approach	2015
64. SWIMS: Semi-supervised subjective feature weighting and intelligent model selection for sentiment analysis	Khan, Farhan Hassan Qamar, Usman Bashir, Saba	Knowledge-Based Systems	AI applications in HRM	Quantitative approach	2016
65. Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making	Mohammad Hossein Jarrahi	Business Horizons	Developing AI definition in HRM	Conceptual approach	2018
66. Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence	Andreas Kaplan. Michael Haenlein	Business Horizons	Developing AI definition in HRM	Conceptual approach	2019

Consent form for recording (Article #2 + 3 (4.2,3))

UNIVERSITAT POLITÈCNICA DE VALÈNCIA

You are being invited to participate in a research study entitled “Artificial intelligence implementation in HR process at the era of COVID 19”. The study is being conducted by Mr Mohand Tuffaha, prof Dr M Rosario Perello-Marin, and Dr Esperanza Suarez-Ruz from Universitat Politécnica de València (Spain). This research is being conducted as a part of thesis of Mr Mohand Tuffaha.

The purpose of this research study is to explore the challenges associated with Artificial Intelligence implementation in Human Resource Management. I anticipate that this interview will take less than 30 minutes to complete.

I appreciate your willingness to help with this project. The data collected will provide useful information for companies to understand the constraints, challenges and opportunities associated with Artificial Intelligence in Human resource management during COVID 19 pandemic. If you would like a summary copy of this study, please let me know at the end of the interview.

If you agree to the term and participate in the study, you will be asked to answer an interview question that could be recorded. A copy of the final script could be provided after the interview if you are interested.

By selecting “I agree” below you are indicating that you have read and understood this consent form and agree to participate in this research study.

I agree to the term and conditions
I disagree

I give consent to my recordings to be included in the aforementioned research project. These recordings could be used in print publications, websites and research purposes.

I have read and understand the conditions and consent to my voice being used as described. If not, my opinions will be treated anonymously.

The researchers are committed to processing information in accordance with the General Data Protection Regulation (GDPR). Personal data collected on this form will be held securely and will only be used for research purposes.

You have the right to request to see a copy of the information we hold about you and to request corrections or deletions of it. You can ask the researcher to stop using it at any time.

Interviewee Name	
Signature	
Date	
If you want your info to be treated anonymously, please mark here a cross	

If you have any questions about this study you may contact to Prof Dr Rosario Perello-Marin at +34 96 387 76 80 (rperell@upvnet.upv.es); or to Mr Mohand Tuffaha at +34 666 729 579 (motuf@doctor.upv.es).

If you are not satisfied with the manner in which this study is being conducted, you may report (anonymously if you choose) any complaints to Departamento de Organizacion de Empresas, Universitat Politecnica de Valencia +34 96 387 76 80.

Thank you for cooperation

Interview questions of the second article (Article #2 (4. 2))

1) Can you please introduce yourself?
2) Can you tell us about the job, the functions that you perform, which are related to the recruitment zone?
3) What is your experience in using chatbots in your recruitment process?
4) What is your current knowledge of chatbots usage in recruitment functions?
5) If we think of chatbots at each stage of recruitment. How chatbots are doing things differently than any other platforms that generally recruiters use.
6) If we walk through the recruitment cycle. Do you think there is any role that chatbots play?
7) Do you see any role that chatbots can play in manpower and job analysis?

   Or it is a human function and it's difficult for chatbots to do anything about it?
8) How do you mention that it enhances the candidate experience? How does it do that?
9) Do you think Chatbots could replace human interaction?
10) How far Indian companies are using chatbots in recruitment?
11) Is there any way chatbots can do the initial interview in India?
12) how chatbots will change recruitment functions in near future in India?
13) Do you think chatbots are not that valuable?

Interview questions of the third article (Article #3 (4. 3))

1- Please introduce yourself and tell me about your job. position title, Number of employees in your company, years of experience and academic background.

2- Please tell me about HR activities where AI is used in your company.

3- Does AI adoption consider a challenge for the companies? Why?

4- From Manager perspective: When and how AI should be provided to HR managers, should AI be offered via internal trainings?

   Or, is it necessary for organizations to appoint AI specialists to work with HR managers in order to adopt AI technology in their activities, policies and practices?

   If AI specialists are appointed, whether the role of specialists might be overlapped with

   managers' decision-making?

5- From the perspective of employees:

   What strategies could HR managers adopt to ensure their subordinates are confident and capable to interact with AI smoothly?

6- In general, what is the optimal strategy for human- smart machine integration?

7- What is the impact of the covid-19 on adopting AI in companies?

8- Do you think there is an adverse impact on accelerating/ deaccelerating emerged technology like AI in companies?