Global Journal of Management and Business Research: A
Administration and Management
Volume 23 Issue 5 Version 1.0 Year 2023
Type: Double Blind Peer Reviewed International Research Journal
Publisher: Global Journals
Online ISSN: 2249-4588 & Print ISSN: 0975-5853

Research on Artificial Intelligence in Human Resource Management: Trends and Prospects

By Dr. Mandeep Kaur, Dr. Rekha AG, Dr. Resmi AG & Dr. Franco Gandolfi
Georgetown University

Abstract- Applying Artificial Intelligence (AI) technologies in Human Resource Management (HRM) contributes to more capability, diverse insights, and analytical support to enhance people management. This study presents an integrated overview of the research trends through a PRISMA-compliant bibliometric review. We have analysed a dataset of 247 Scopus-indexed publications between the earliest available date (1993) till 2020 to understand the key themes and the related research focus. The study shows that most research has been conducted in recent years, with 70% of relevant papers published since 2010. The key themes subscribed to the development of this literature have been called out. The outcome of term co-occurrence analysis highlights majority research related to AI in HRM focuses on resource allocation, talent acquisition, and training and development. The research spotlights significant areas attributed to AI in HR functions that warrant additional research. Deliberation of research gaps and recommendations on future direction is also provided.

Keywords: artificial intelligence, AI, HRM, human resource management, bibliometric analysis.

GJMBR-A Classification: LCC: HD28-HD70

RESEARCHONARTIFICIALINTELLIGENCEINHUMANRESOURCEMANAGEMENTTRENDSANDPROSPECTS

Research on Artificial Intelligence in Human Resource Management: Trends and Prospects

Dr. Mandeep Kaur [α], Dr. Rekha AG [σ], Dr. Resmi AG [ρ] & Dr. Franco Gandolfi [ω]

Abstract- Applying Artificial Intelligence (AI) technologies in Human Resource Management (HRM) contributes to more capability, diverse insights, and analytical support to enhance people management. This study presents an integrated overview of the research trends through a PRISMA-compliant bibliometric review. We have analysed a dataset of 247 Scopus-indexed publications between the earliest available date (1993) till 2020 to understand the key themes and the related research focus. The study shows that most research has been conducted in recent years, with 70% of relevant papers published since 2010. The key themes subscribed to the development of this literature have been called out. The outcome of term co-occurrence analysis highlights majority research related to AI in HRM focuses on resource allocation, talent acquisition, and training and development. The research spotlights significant areas attributed to AI in HR functions that warrant additional research. Deliberation of research gaps and recommendations on future direction is also provided.

Keywords: artificial intelligence, AI, HRM, human resource management, bibliometric analysis.

I. Introduction and Background

Rapid increase in digitization and the corresponding trend of leveraging Artificial Intelligence Technologies (AIT) has been reshaping the business landscape.The amalgamation of Information Technologies and Human Resource Management (HRM) has brought forth improved efficiency, impacted service delivery, provided standardization, empowered managers, and transformed HR functions (Parry and Tyson, 2011; Bondarouk and Brewster, 2016). AI and related technologies, be it Machine Learning (ML), Robotic Process Automation (RPA), or Natural Language Processing (NLP), have influenced and revolutionized the very foundation of business models (Heric, 2018). The transformation of HR technologies has also revolutionized HRM practices by introducing functionalities of e-recruitment, e-training, or e-competence management (Stone et al., 2015). AI-enabled digital technologies have impacted HR functioning approaches such as resource planning, candidate sourcing, talent acquisition, attrition prediction, performance evaluation, succession planning, employee engagement, compensation, and learning and development (Kovach & Cathcart, 1999; Falletta, 2013; Rogers, 2018; Fallucchi et al., 2020; Kaur et al., 2021). HR function has transitioned from being considered a support function, to being acknowledged as a strategic partner to the business (Park, 2018; Zehir et al., 2020). Therefore, in the current context of rapid digitalization, the expectation is to adopt contemporary technological advances to build additional digital and cognitive HRM competencies that will enhance business performance. HR is envisaged to be a 'key transformation player' in the adoption of technologies and in reducing resistance to change (Thite, 2018).

Literature indicates the growing importance of AI tools for HRM activities. These technologies have enabled new functionalities in HRM, such as, data mining, cloud computing, application of HRM for mobile technologies, Social Media, Analytics, Clouds (SMAC), and big data (Bondarouk, 2014). A conceptional framework of AI in HRM is proposed in a study by Jia et al. (2018), which consists of aspects of HRM related to talent acquisition, learning, HR strategy, performance management, compensation, and employee engagement along with related AI technology applications. AI strengthens HRM functionality to identify actual performers and future leaders by eliminating bias (Buck and Morrow, 2018). Another key aspect is contribution of AI in enhancing employee experience (Smith, 2019). AI applications em powers HR teams to make better talent decisions in analysing, predicting, and diagnosing, thus providing a strategic advantage (Nicastro, 2020).

Work and the HR function are going through a period of rapid change and are getting transformed by technological advancements (Bondarouk et al., 2017, Connelly et al., 2020). The innovation and related disruptions in business processes require continuous up-skilling of employees. As a function, HR has needed to reimagine how work needs to be done differently with AI and the related technologies (Manuti and Palma, 2018; Maity, 2019). The digitization of HR has been referred to by many terms – online HRM, E- HRM, and digital HRM (Crawshaw et al., 2020). On challenges of AI in HR, Tambe et al. (2019) emphasize the challenges

Author α: Director-HR, Kyndryl Corporation. 212 Eglinton Avenue East, Suite 1103, Toronto M4P A03, Canad.
e-mail: mandeep.caur@gmail.com
Author σ: IT & Systems Specialist, State Bank of India. Digital & Transaction Banking Unit, LHO Thiruvananthapuram, Kerala, India - 695012. e-mail: agrekha64@gmail.com
Author ρ: Associate Professor, TKM Institute of Management, Kollam, Kerala, India- 691005. e-mail: resmi.agr@gmail.com
Author ω: Distinguished Professor of Management, California Institute of Advanced Management (CIAM) & Georgetown University, Washington DC, USA. e-mail: francogandolfi@hotmail.com

related to limitations imposed by small data sets, the intricacy of HR phenomena, aspects of fairness, ethical, legal, and accounting aspects in the adoption of AI in HR. There are various challenges ranging from empirical to conceptual, which can be attributed to the adoption of AI in HRM (Kaur et al., 2021).

Thus, AI has become progressively of great interest to scholars and practitioners.The impact of AI on HRM has necessitated the need for conducting an exhaustive study of the research landscape of this critical domain. It appears from the literature that the research on applications of AI in HRM is receiving a greater focus and many related relevant areas remain unexplored. The current study has attempted to provide insights to the following research questions (RQs):

RQ1: What are the research trends of publications in terms of source types, citations, document types etc. related to AI in HRM?

RQ2: What are the key themes of research in the domain of AI in HRM?

RQ3: Which are the areas/domains that require additional and focused examination in the future related to AI in HRM?

This study was conducted using bibliometrics analysis to provide reference, insights, and inputs for future research and to share in-depth insights into aspects of AI-HRM research trends with the Scopus database as the base.

This paper is arranged into five sections. The following section briefs the methods, data and the search strategy used in this study. Then we present the analysis and findings of the study. After that we provide a detailed discussion on major research themes identified and the future research directions followed by concluding remarks.

II. Methodology

a) Method

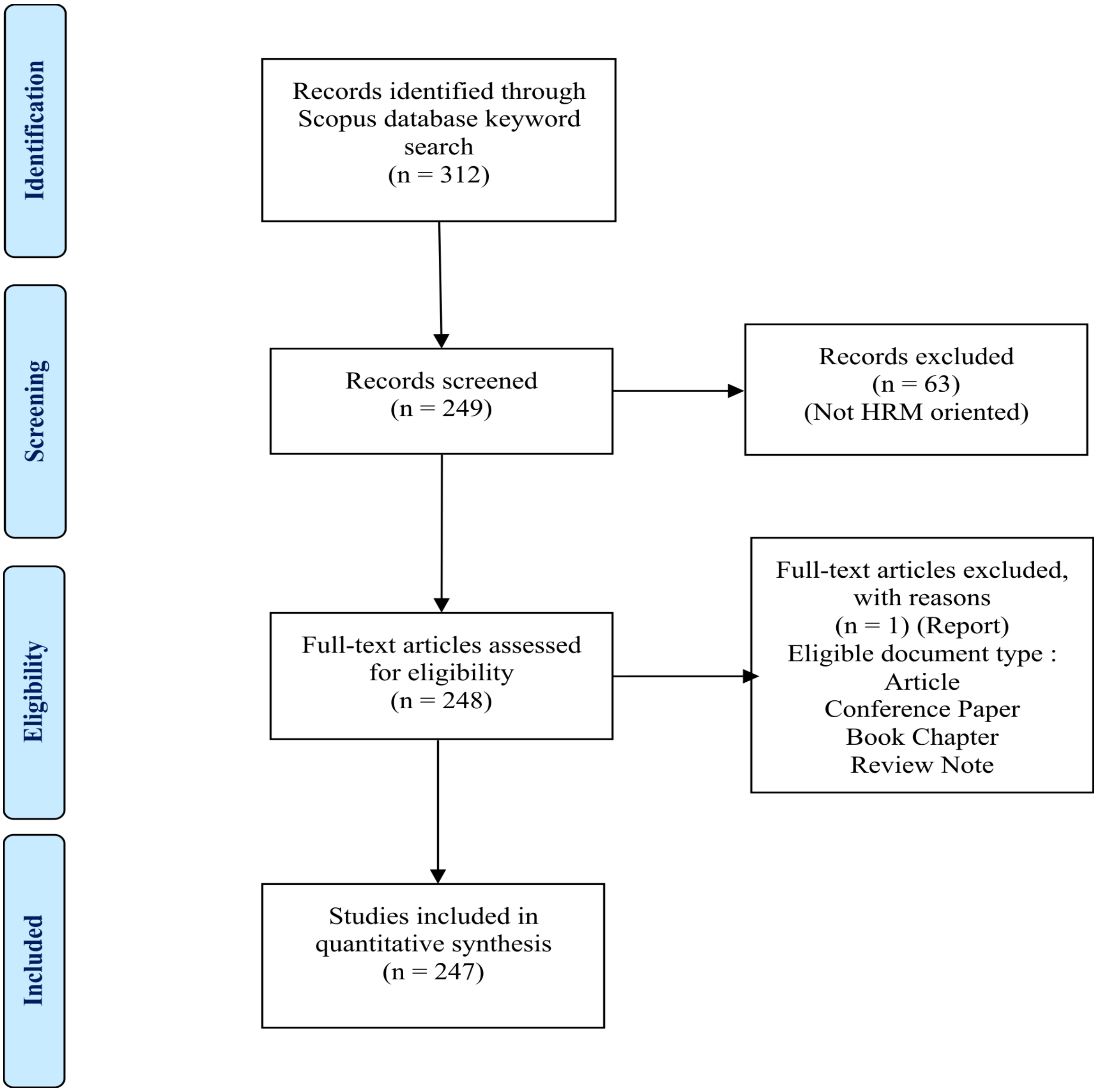
Bibliometric analysis has been widely recognized as one of the significant methods to determine and forecast the research trends of specific topics (Zupic and Cater, 2015). Bibliometric analysis-based studies include methods for understanding the global trends in research within a particular field using a database of scholarly literature and presents findings and discussions on the evolution and intellectual structure of knowledge base in that field. In this study, we conducted a bibliometric analysis using citation analysis, co-citation analysis, keyword co-occurrence analysis, and clustering (Ellegaard and Wallin, 2015; Linnenluecke et al., 2020; Donthu et al., 2021). The following section presents the data source and search strategy applied in this study.

b) Data Source

Scopus is a detailed database with adequate inbuilt search filters (Oliveira et al., 2019). Thus, we have earmarked Scopus as the data repository to pull out relevant results related to the research. All related studies published and indexed in Scopus till the end of the year 2020 has been reviewed to document and analyse key trends since the emergence of research related to AI in HRM.

c) Search Strategy

Systematic methods were deployed in the research by adopting the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) guidelines to make the article selection process to be objective and systematic (Priyashantha et al., 2021). As represented in the flow diagram (Figure 1), we have followed a search protocol and inclusion/exclusion criteria through the four steps of identification, screening, eligibility and inclusion for arriving at the list of articles to be analysed as mentioned in Meline (2006) and Pahlevan-Sharif (2019). The study integrated an extensive range of document types, indexed by Scopus, including books, chapters/ sections of books, journal articles, and conference papers published by 2020 on the topic. As there was no specific start date being referenced for the Scopus search in the literature, thus it facilitated the search engine to identify the earliest studies related to this topic. After the initial screening of documents from a relevant perspective, the final database reflected a total of 247 documents, resultant of query results by using keywords "Human Resource" OR "HRM" OR "Talent" OR "Personnel Management" OR "HRD" AND "AI" OR "Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Neural Network" OR "Fuzzy" OR "ANN" OR "Genetic Algorithm" OR "Predict". Additionally, all available metadata related to the title, abstract, keyword, and related research studies were downloaded and analysed. Additional data editing was conducted for specific fields of the search, which included instances wherein synonyms were merged (e.g., 'Human Resource Management, 'Human Resources Management' and 'HRM'). The quantitative review aimed to examine the present status of literature related to AI in HRM and to recognize, identify, and trace clusters and integrated research.



Source: Moher et al., (2009)

Figure 1: Prisma Flow Diagram detailing Steps in the Identification and Screening of Sources

III. Analysis and Findings

On the research question (RQ1), we analysed the key attributes of the literature and research trends currently on AI in HRM. A total of 247 Scopus-indexed documents spanning the last 25 years represent a rapidly increasing foundation of knowledge related to AI in HRM. The source type represented in Table 1 reflect that journal papers contributed to 49.80% of the published documents on AI research in the HRM domain, while conference papers contributed 39.68% and book series 9.72%. Table 2 represents citation metrics, and it shows that there is an average of 68 citations per year.

Table 1: Publications by Source Type

Source Type	Total Publications (TP)	Percentage (%)
Journal	123	49.80%
Conference Proceeding	98	39.68%
Book Series	24	9.72%
Book	1	0.40%
Trade Journal	1	0.40%
Total	**247**	**100%**

Source: Scopus Database;1993 to 2020 and Authors Compilation

Table 2: Citations Metrics

Metrics	Data
Publication years	1993-2020
Citation years	27 (1993-2020)
Papers	247
Citations	1859
Citations/year	68
Citations/paper	7
Citations/author	708
Papers/author	120
h-index	2
g-index	23

Source: Scopus Database; 1993 to 2020 and Authors Compilation

Table 3: Publications Bylanguage

Language	Total Publications (TP)	%
English	239	96.76%
Chinese	5	2.02%
German	1	0.40%
Portuguese	1	0.40%
Spanish	1	0.40%

Source: Scopus Database; 1993 to 2020 and Authors Compilation

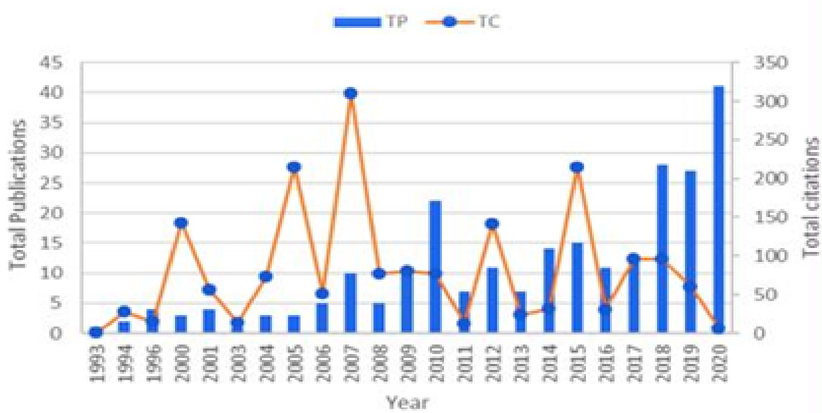
Table 4: Countries with Highest Number of Documents Published (Country of Origin)

Sl	Country	TP	%
1	China	106	42.74%
2	Taiwan	17	6.85%
3	India	14	5.65%
4	Iran	13	5.24%
5	United States	11	4.44%
6	Turkey	9	3.63%
7	United Kingdom	9	3.63%
8	Germany	7	2.82%
9	Brazil	6	2.42%
10	Malaysia	6	2.42%

Source: Scopus Database; 1993 to 2020 and Authors Compilation

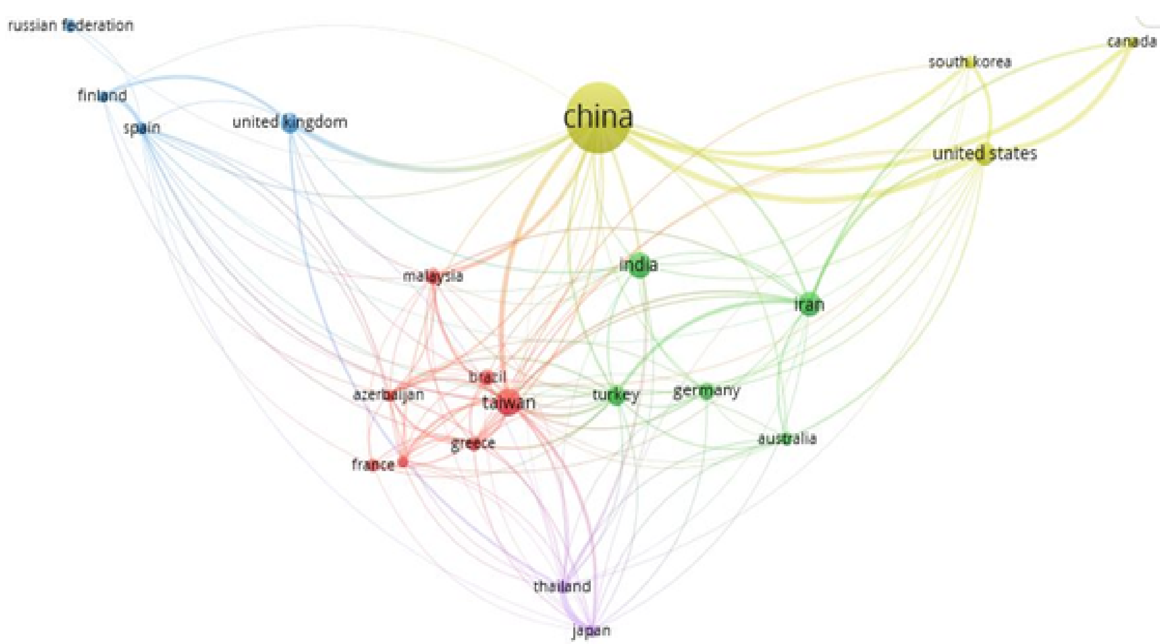
Figure 2 traces the growth trajectory of the number of publications related to the area of AI in HRM till October 2020. During the period from 1993 to 2010, 30% of contributions of the total publications were made, while during the last decade, i.e., during the period 2010 to 2020, 70% of the publications were made. The sharp increase reflected in publications from the year 2018 contributing to 44% of the total publications since 1993, indicates the increasing focus on the application of AI in the HRM function. The analysis of the language of research publication is reflected in Table 3, with English contributing to the majority 96.7%, followed by 2.02% as Chinese, and German, Portuguese and Spanish at 0.40% respectively. Table 4 represents the countrywide distribution of research indicating that 42.74% of the documents are published in China, followed by Taiwan with 6.85% and India with 5.65% of the contribution. The figures suggest that there is an upward swing reflected, with swiftly emerging literature since 2018.

Year	TP %	Cumm %
1993	0%	0%
1994	1%	1%
1996	2%	3%
2000	1%	4%
2001	2%	6%
2003	0%	6%
2004	1%	7%
2005	1%	9%
2006	2%	11%
2007	4%	15%
2008	2%	17%
2009	4%	21%
2010	9%	30%
2011	3%	33%
2012	4%	37%
2013	3%	40%
2014	6%	46%
2015	6%	52%
2016	4%	56%
2017	5%	61%
2018	11%	72%
2019	11%	83%
2020	17%	100%



Source: Scopus Database;1993 to 2020 and Authors compilation

Figure 2: Total Publications by Year Notes: TP=total publications; TC=total citations. TP %=percentage of publications; Cumm%=cumulative percentage of publications.



Source: Generated by the Authors using VOS Viewer

Figure 3: Country-Based Bibliometric Coupling

Table 5: Top Author Keywords Used in the Literature

Author Keywords	Total Publications (TP)	Percentage (%)
Human Resource	96	38.87%
Artificial Intelligence	47	19.03%
Fuzzy Logic	43	17.41%
Decision Making	42	17.00%
Resource Allocation	37	14.98%
Neural Networks	25	10.12%
Analytic Hierarchy Process	22	8.91%
Artificial Neural Network	16	6.48%

Optimization	14	5.67%
Personnel Training	14	5.67%
Genetic Algorithms	12	4.86%
Hierarchical Systems	12	4.86%
Performance Evaluation	12	4.86%
Enterprise Human Resource	10	4.05%
Recruitment	10	4.05%
Deep Learning	9	3.64%
Fuzzy Evaluation	9	3.64%
Genetic Algorithm	9	3.64%
Talent Management	8	3.24%
Decision Support Systems	7	2.83%
Decision Theory	7	2.83%
Fuzzy Systems	7	2.83%
Human Resource Allocation	7	2.83%
Innovation	7	2.83%
Machine Learning	7	2.83%
Membership Functions	7	2.83%
Neural Network	7	2.83%
Project Management	7	2.83%
Analytical Hierarchy Process	6	2.43%
Big Data	6	2.43%

Source: Scopus Database; 1993 to 2020 and Authors Compilation

Figure 3 represents country-based bibliometric coupling, indicating that the countries presented therein cite similar literature in their publications. Higher bibliometric coupling indicates that the studies deal with related subject matter (Martyn, 1964). The figure shows that strongest bibliometric coupling exists between China and the United States, indicating that the studies originated from China and the United States have common citations more frequently. Table 5 is representative of the main keywords related to AI in HRM, which indicate the functionalities and technologies associated with AI in the HRM field that is currently being referenced in research. These keywords related to functionalities are – "decision making", "resource allocation", "optimisation", "personnel training", "performance evaluation", "talent management". The corresponding keywords related to AI technologies are – "neural networks", "genetic algorithms", "deep learning", "fuzzy support systems".

Table 6: Literature Related to Cluster 1: AI in Resource Allocation

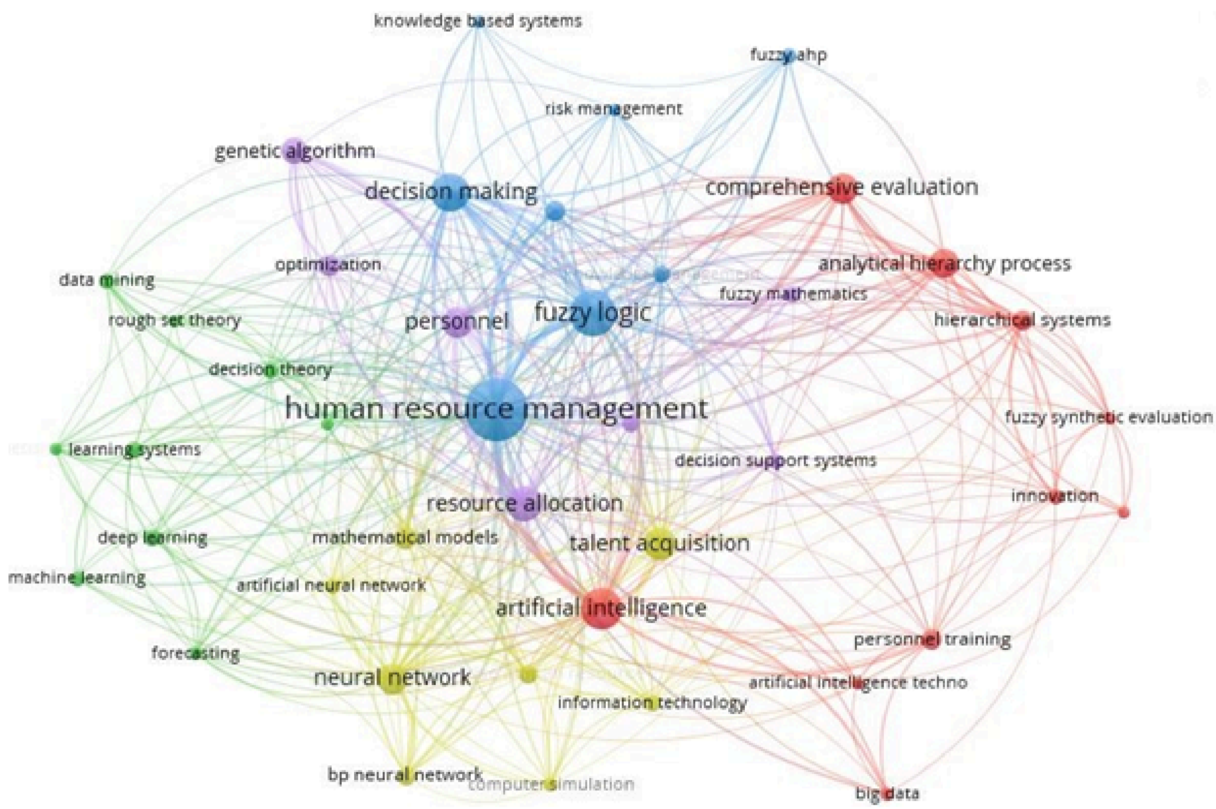
Research on HRM Functionality/AI Technique	Research Sources
Demand forecasting, Allocation of resources, Prediction tasks, Neural Networks applications, Analytic Hierarchy Process, Fuzzy Mathematics	Aviso et al.(2018);Andalib et al.(2020);Apornak etal.(2021);Coelho et al.(2019);Chang (2010); Ivanov et al.(2020); Kieling et al.(2019); Khanizad & Montazer (2018); Kwak & Jung, (2003); Markevich & Sidorenko (2019); Xu et al.(2019)
Prioritization of resource demands, Resource optimization	Daojin (2010); Guenole & Feinzig (2019); Hsu et al. (2019); Lin & Gen (2008)
Reverse candidate profiling, Ideal Fit for role, Balanced Job descriptions, AI Algorithms	Gikopoulos(2019); Guenole & Feinzig (2019); Rogers (2018); Leem (1996)

a) *Term Co-Occurrence Analysis*

In order to identify the research focus, a co-occurrence analysis was conducted of all keywords, including author keywords and index keywords, using VOS viewer software (Van Eck and Waltman, 2010). As reflected in Figure 5, areas of maximum focus in the research related to AI in HRM literature are talent acquisition for recruitment and selection, resource allocation, and personnel training. The analysis also reflects the related AI technologies that support these functionalities: machine learning, data mining, big data, deep learning, neural network, and fuzzy logic.

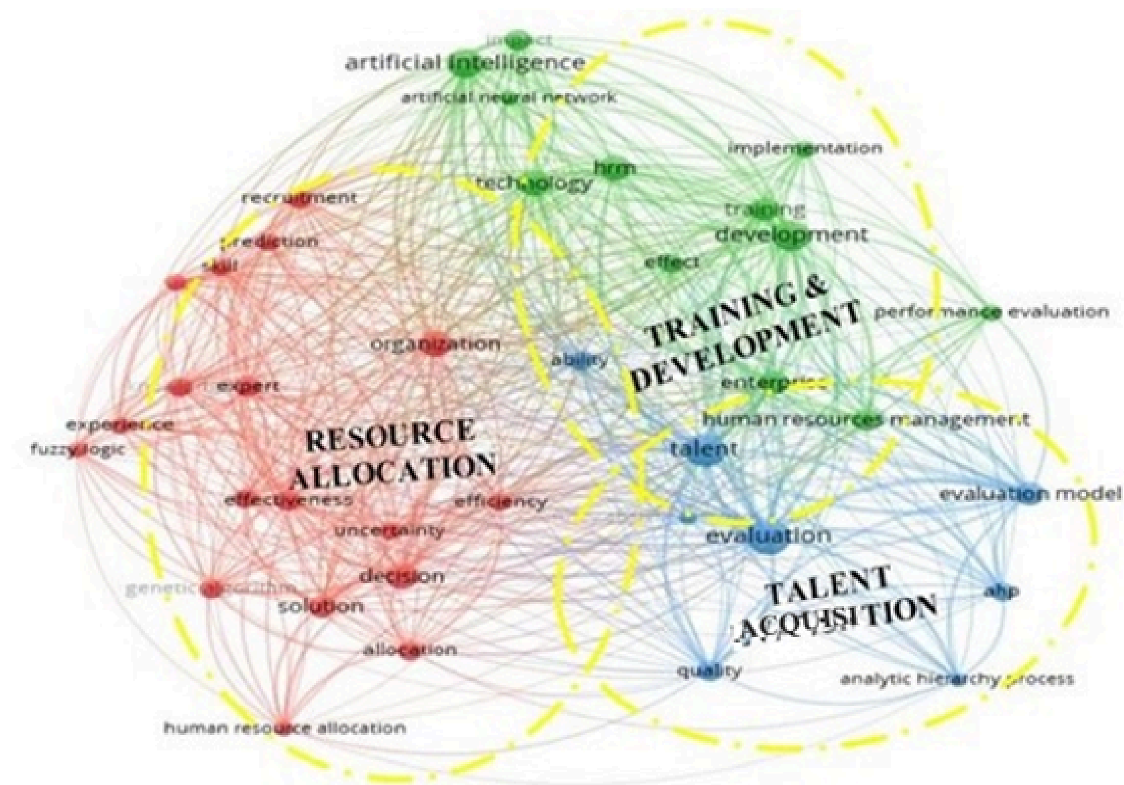
Co-occurrence network (Figure 5), based on title and abstract fields, indicates that the significant overlapping areas in AI in HRM research are resource allocation, training & development, talent acquisition, and related aspects of efficiency and effectiveness in decision-making. It is also indicative that the methods and techniques focussed include analytic hierarchy process, artificial neural network, fuzzy logic, and evaluation models. Resource allocation function is facilitated by the application of AI in HRM, as it contributes in an optimal, effective, and budgeted manner, the process of assigning and scheduling available resources, including the workforce. The talent evaluation function is objectively developed and driven by neural networks and the analytic hierarchy process, which brings forth a method of organizing and analysing complex decisions related to talent. Training and development are another key area that is reflected in the co-occurrence network.

The second research question (RQ2) focussed on the areas of research in the domain of AI in HRM. As indicated in the VOS viewer visualization of term co-occurrence network based on title and abstract (Figure 5) suggests that the research in AI in HRM predominantly focuses on talent acquisition, resource allocation, and training and development. Top keyword analysis, as reflected in Figure 4 shows the prominent keywords used in the publications, bigger a circle, the more frequently the keyword appears in the publication set from Scopus. The top three keywords as per the analysis are Human Resources (38.87%), AI (19.03%), and Fuzzy Logic (17.41%). A brief overview of the literature on the three key areas identified, namely, resource allocation, talent acquisition, and training and development is reflected in Tables 7, 8 and 9.



Source: Created by Authors using VOS Viewer

Figure 4: Network Visualization Map of Keywords



Source: Created by Authors

Figure 5: VOS Viewer Visualization of Term Co-Occurrence Network based on Title and Abstract (Binary Counting)

Table 6: Literature Related to Cluster 1: AI in Resource Allocation

Research on HRM Functionality/AI Technique	Research Sources
Demand forecasting, Allocation of resources, Prediction tasks, Neural Networks applications, Analytic Hierarchy Process, Fuzzy Mathematics	Aviso et al.(2018); Andalib et al.(2020); Apornak etal.(2021); Coelho et al.(2019); Chang (2010); Ivanov et al. (2020); Kieling et al.(2019); Khanizad & Montazer (2018); Kwak & Jung, (2003); Markevich & Sidorenko (2019); Xu et al.(2019)
Prioritization of resource demands, Resource optimization	Daojin (2010); Guenole & Feinzig (2019); Hsu et al. (2019); Lin & Gen (2008)
Reverse candidate profiling, Ideal Fit for role, Balanced Job descriptions, AI Algorithms	Gikopoulos(2019); Guenole & Feinzig (2019); Rogers (2018); Leem (1996)

Table 7: Literature Related to Cluster 2: AI in Talent Acquisition

Research on HRM Functionality/AI Technique	Research Sources
Sourcing candidates. Predictive tool algorithms for programmatic recruitment advertising	Esch & Black (2019); Schweyer (2018)
Candidate engagement through chatbots on the web, mobile, socially enabled by natural language processing	Ernst & Young (2018); Meister (2019a); Nunn, (2019); Sheikh et al.(2019); Upadhyay & Khandelwal(2019)
Candidate profiling by applying computational linguistics	Charlier & Kloppenburg (2017); Walford-Wright & Scott-Jackson (2018)

Profile matching,Automation of resume/job description, Optical character recognition (OCR), Advanced application tracking systems, Inclusive AI algorithms for unbiased screening of profiles	Barboza (2019); Cohen (2019); Esch & Black (2019); Gikopoulos (2019); Guenole & Feinzig (2019); Kaplan & Haenlein (2019); Meister (2018b); Nunn (2019); Rogers (2018); Sivathanu & Pillai (2018); Strohmeier & Piazza (2015)
Talent selection techniques, Neural network, Fuzzy Systems, Data mining techniques,Gaming techniques for selection, AI chatbots – interpretation/validation of candidate response	Bersin (2017); Huang et al.(2001,2004); Ranjan et al. (2008); Sivathanu & Pillai (2018); Ernest & Young (2018); Meister (2018b); Mentzelopoulos & Economou (2020); Johnson et al. (2020); Jimenez et al.(2018); Qin et al. (2020); Ye et al.(2019)
Interview methods with Unconscious bias reduced -AI tools "listen"/prompt question, Robotic Process Automation (RPAs)	Cohen (2019); Gikopoulos (2019); Guenole & Feinzig 2019); HRPA (2017)
Onboarding, Natural language processing, for chatbot-agnostic technology and text-based conversational interface of Chatbots as an online buddy, customization, and automation, and core business functions, AI algorithms to map team fit,learning needs on Day 1	Barboza (2019); Gikopoulos (2019); Upadhyay & Khandelwal (2019)

Table 8: Literature Related to Cluster 3: AI in Training & Development

Research on HRM Functionality	Research Source
AI tagging of learning content through metadata, AI-enabled tutoring systems, intelligent agents embedded	Barboza (2019); Guenole & Feinzig (2019); Meister (2019a); Niehueser & Boak (2020); Schweyer (2018); Qiong et al. (2018)
Individual Development Plan, Succession Planning Smart data matching and AI-enabled Individual profile analysis to identify the right talent for key roles	Barboza (2019); Bersin (2017); Nunn (2019)
Career mobility through digital coaching Virtual assistant-datafor personalized career counselling.	Bersin (2017); Ernest & Young (2018); HRPA (2017); IBM (2019);Kiron & Spindel (2019)
Skill gap analysis, Gaming techniques for Deep Learning, Current analytics, and predictive analytics of skills required	Barboza (2019);Guo & Li (2020); Nunn, (2019a); Mentzelopoulos & Economou (2020);

The effectiveness of HR function is greatly enhanced by the adoption of AI and the associated technologies. The third research question (RQ3) addresses the areas/domains that require additional and focused research in the future related to AI in HRM. There has been a steady pace of development of applications related to AI technologies for the HRM function, which have been covered with adequate research.

IV. Discussion and Future Research Directions

The analysis shows that a significant portion of the research was published during the last decade, with a sharp increase since 2018. In the country-wise publication output, China is leading with more than 42% of documents published in the area of AI in HRM. As pointed out in (Demchak, 2019; Li et al., 2021), China is abundant with the two critical assets needed in the AI era, i.e., data and engineering talent, which could be the reason behind its prominence in this field. The keyword and term co-occurrence analysis were conducted to explore the prevailing themes in the research related to AI in HRM. Three clusters emerged from the term co-occurrence analysis based on title and abstract is represented in Figure 5. A brief discussion on these clusters is presented in the following sub sections.

a) Cluster 1 - Resource Allocation

The logical allocation of human resources plays an important role for the organization's development and is considered a challenge by many organizations. The term co-occurrence network showed that workforce planning and resource management are a key research area in AI and HR. Literature suggests that AI technology and applications enable organizations for efficient workforce management and optimization. For example, a variation of unsupervised Competitive Learning neural networks algorithm was proposed by Leem (1996) to overcome the obstacles that conventional analyses face. The deployment of Analytic Hierarchy Process (AHP) and Fuzzy Mathematics systems ensures appropriate management decisions for employees' most suitable role assignments (Subramanian and Ramanathan, 2012; Saaty et al., 2007). A fuzzy input-output optimization method was proposed by Aviso et al. (2018) for HR allocation during a crisis.

AI enables a comprehensive evaluation of human resource allocation and continuous improvement. The ability of AI to analyze a large amount of data and draw inferences and detect patterns assist in resource planning optimally (Lengnick-Hall et al., 2018). It also enables multi-criteria human resource allocation, which involves allocating limited availability human resources among many demands by optimizing current objectives (Lin & Gen, 2008). Data related to employee performance and succession and analysis of it provides insights on employee engagement and related challenges (Smith, C. 2019). Resource efficiency can be enhanced by forecasting, which is critical in decision making, based on which the financial costs of the workforce can be optimized.

b) Cluster 2 - Talent Acquisition

Literature shows that AI enhances recruitment efficiency through balanced job descriptions, job requisition prioritization, profile databases, programmatic recruitment advertising based on machine learning, attracting potentially suitable candidates (Albert, 2019; Upadhyay and Khandelwal, 2018). A human resource selection system constructed using FNN is discussed in Huang et al. (2004). AI assistants support the engagement of candidates through digital platforms (Van and Black, 2019). Specialized chatbots can be used for candidate attraction and to have an insightful conversation to engage candidates in deeper conversation and recommend jobs relevant to their skills and experience (Leong, 2018). The chat topics provide informative answers about aspects related to the organization – compensation, vacation guidelines, culture, locations, dress code, business, and assessment process. It enhances the scope of converting prospective candidates into active job seekers. Thus, creating a positive recruiting experience and facilitates accepting a job offer by the right candidate. Selection efficiency is improved by proper candidate identification with data analysis (Bongard, 2019). Predictive analysis helps forecast the future performance of a prospective candidate, basis the profile and information collated and analysed during the automated aspects of the job application process.

Profile matching, Optical Character Recognition (OCR), CV Parsing are key applications enabled by AI (Singh and Finn, 2003; Bizer et al., 2005). Initial screening can be automated by neural networks, data mining techniques, and AI chatbots by conducting interpretation/validation of candidate responses. Intelligent interviews are conducted with reduced unconscious bias, assisted by AI tools to "listen"/prompt questions and Robotic Process Automation (RPAs) (Madakam, 2019; Nawaz, 2019). Background checks are automated, based on different reviews required, basis the profile of the candidate. From the literature it can be seen that the digitally enabled on boarding process focuses on two aspects. One is to automate, and the second is to personalize. Functionalities like Chatbots support new hires in knowing relevant details about their new role, team hierarchy, and overall organizational landscape (Ernst & Young, 2018; Nunn, 2019). The efficiency of the on boarding process improves by the collection of employee information, joining forms completion, and assistance in online registration. Another key aspect is that through digitally enabled on boarding, the new hires have access to tools facilitating them to connect and socialize in their new organization, which positively impacts their learning, productivity, and engagement, as they settle in their new roles (Sheikh et al., 2019;Upadhyay & Khandelwal, 2019).

c) Cluster 3 - Training and Development

Cluster 3 focuses on training and development applications of AI. Literature suggests that AI-based tools provide more personalized and enhanced digital learning experience (Ong and Ramachandran, 2003; Maity, 2019). An employee can access their skill profiles, to build their skill journey helping to have ownership in building their skills path and their career path and thereby supporting the acceleration of skill development (Wang and Lin, 2020). The search engine capabilities in the Learning tools architecture helps in making intelligent recommendations, for the learning road map, for an employee. Through metadata, AI tagging of all content in the learning modules supports user-friendly interfaces through content channels (Guenole and Feinzig, 2019). Intelligent data matching and AI-enabled individual profile analysis provide insights that help identify the right talent for key roles and succession planning (Barboza, 2019; Bersin, 2017; Nunn, 2019). Interactions with employees for growth and future opportunities are enabled by AI tools, which can act as a personalized digital career advisor, allowing employees to advance their careers within the organization. This allows in creating meaningful work experiences for employees, better growth assistance, and building more robust pipelines for critical businesses. The interactive user interface uses natural language processing to engage in active discussion with the employees (Litman, 2016). This is integrated with precisely the employee's historical information about various aspects. Literature also suggests that AI-enabled job-opportunity match functionality will be of use in suggesting suitable roles for employees, based on their profiles (Tambe, 2019; Nocker and Sena, 2019). Employee queries can be resolved by the AI tools. Provision of built-in alerts on job opportunities help employees to know about internal opening matching to their current profiles and tailored to their aspirational roles.

We can see that majority of research related to AI in HRM focuses on talent acquisition, resource allocation, and training and development. Very few studies have explored the adoption of AI in other HR functions such as employee retention, compensation and seperation. Additional research is needed on different aspects of AI in HRM, including adoption challenges, impact studies, new skill requirements etc. In the following section, we discuss the future research directions based on the findings.

d) Implications and Future Research Directions

As indicated by the findings, despite continual research progress is being made related to AI technologies for the HRM function, there are areas which need further attention and in-depth understanding.

The study findings indicate possible follow-on ideas and future studies. For example, research is required on how AI and related technologies in the HRM function have impacted vital aspects of employee engagement, retention, growth, compensation, reward, and recognition. There have been very few studies conducted related to these aspects. How this phase of HR transformation and the strategic development of HR has impacted business performance is a key area that has not been investigated.

The transformation of HR function by the adoption of AI technologies is an emergent field of focus. Despite the benefits of AI adoption, there is a huge variance in terms of adoption of AI. Research needs to be conducted on what are the influencing factors that impact adoption. Though AI adoption is key aspect of technology adoption in organizations, there is lack of technology adoption model-based research, related to adoption of AI across all domains of HR. Further, detailed research work is recommended to be conducted on the design and implementation of change management in adoption. Another good avenue for future research would be industry-specific and cross-industry comparisons to support further research.

Many areas merit additional investigation, even though a significant work on AI in HRM has been conducted, especially in the last decade. AI in HR has enabled the HRM function to be transformed and acknowledged as a strategic partner of the business. For example, technological advancements have created opportunities in the talent acquisition domain that links strategic HR management with business strategy (Walford and Scott, 2018). By enabling digital engagement, HR provides a competitive advantage to the organizations (Jesuthasan, 2017). There is a lack of research, as to what is the impact of HR's transformation by leveraging AI and how does this contribute to enabling organizations to achieve business success and leverage strategic advantage for hiring and retaining key talent. Further, in the domain of strategic HRM, cognitive enabled insights can facilitate drawing optimal outcomes. While humans contribute to a more thorough and intuitive approach to managing uncertainty and complexity in organizations (Jarrahi, 2018), AI can enhance humans' cognition when handling complex problems. There is a dearth of research and detailed studies on this aspect.

The use of AI tools/applications has led to questions related to the authenticity of people/talent decisions made basis AI algorithms and logic. Especially in the talent acquisition domain, the fairness and objectivity of hiring decisions based on the logic of an AI based algorithm or an AI based decision rule is questioned, as to whether these decisions are objective (Bogen, 2019). Aspects regarding the authenticity of employee data – both current and potential, are a cause of concern, as its validity is questionable. The authenticity of algorithms designed based on the data could be imperfect, as it could reflect society's ingrained prejudices and biases. Also, the aspect of inherent or unconscious bias which could be part of the logic of the algorithm or seeded in the decision rule and driving biased decision related to hiring needs further exploration. Data sets could be structured in advance to be aligned with historical precedents and patterns, which could even be part of an organization's culture and can be hardwired into code (Gulliford and Dixon, 2019). Questions regarding talent decisions made basis this data, whether it further strengthens exclusions and existing biases, is imperative to be researched, as these are sensitive topics to be addressed. Also, interlinked to this, there is a requirement for more comprehensive insights and counsel in the form of additional research to help address ethical concerns and acceptance of talent decisions based on applications of AI in the human resources functions.

Concerns related to the security and privacy of employee sensitive information also needs deeper exploration. Capelli (2019) has highlighted some of the drawbacks of data science being applied in HR, including concerns related to infringing on privacy, usage of social media posts as a determinant factor for hiring, which may lead to discriminative impacts on minorities/diversity. Democratizing data, transparency, and providing data and insights to employees is another aspect that needs further exploration (Hirsch, 2019).

Practical implication of the findings is related to the skill development of HR practitioners. There is lack of research regarding a key aspect, which is related to the expectations of new skills and competencies that HR professionals need to be proficient in, to adopt and apply AI and leverage its benefits. The skills of present and future HR practitioners will need to be developed to manage today's AI applications and future advancements. HR practitioners need to learn how to use AI-enabled analytical tools. They also need to be able to interpret and take action basis the analysis, thus developing numerical analysis and reasoning skills will also be required (Davenport, 2019). HR professionals need to have the competence to utilize technology to provide insights that support business, which necessitates the skill development of HR professionals (Wang and Lin, 2020). There are hardly any studies conducted on this key aspect of AI in HRM, which is the new skills and competencies that HR professionals need to be proficient in adopting and applying AI applications in HRM and leveraging all the benefits. Recent studies indicate that COVID-19 may accelerate the adoption of AI in HRM (Hamouche, 2021; Vahdat, 2021; Khalifa, 2022). There is also research gap related to actual impact studies providing insights on the adoption of AI and related technologies on the transformation of HR, which can be potentially leveraged for future growth and advancement of the HR function.

V. Conclusion

The adoption of AI in HRM has resulted in the effectiveness of HR processes, service delivery, and enhanced employee experience. It is imperative to study and interpret the further trends and opportunities of AI as applied to HRM. This work provides an exhaustive study of the emergence and accelerated growth of research on AI in HRM. We have evaluated the current status of research in the domain of AI in HRM and demonstrated the research gaps. In general, studies directly addressing AI in HRM in the abstract, title, or keywords has been continuously growing since 2010. The growth trajectory of literature indicates that it has more than doubled in size over the past decade. Analysis related to various aspects of research, be it types of documents and volume of documents, conceptual coherence, and citation impact, reveals that the most prevalent research areas are talent acquisition, resource allocation, and training and development in applying AI in HRM. Other predominant areas of research highlighted are neural networks, fuzzy logic, and evaluation models. Various future research implications are also discussed. Though this study has limitations in that it has considered only the publications indexed by Scopus, the comparatively small amount of research articles directly addressing the field suggest that further research is needed, focusing on areas of systematic theory development as well as conceptual and empirical studies. AI in HRM, being a rapidly developing area, there is substantial literature and research in the form of white papers and industry reports, which may lead to a lack of requisite bibliographic control.

References Références Referencias

1. Albert, E. T. (2019). AI in talent acquisition: a review of AI-applications used in recruitment and selection. *Strategic HR Review*, *18* (5), 215-221.
2. Andalib, T. W., Halim, H. A., & Islam, M. K. (2020, February). *Coding mechanism and soft systems technique applied to integrate the fuzzy based Decision Support System with HRM factors in the SMEs of Bangladesh.* IOP Conference Series: Materials Science and Engineering. *769* (1), 012042. IOP Publishing.
3. Apornak, A., Raissi, S., Keramati, A., & Khalili-Damghani, K. (2021).Human resources optimization in hospital emergency using the genetic algorithm approach. *International Journal of Healthcare Management*, *14* (4), 1441-1448.
4. Aviso, K. B., Mayol, A. P., Promentilla, M. A. B., Santos, J. R., Tan, R. R., Ubando, A. T., & Yu, K. D. S. (2018). Allocating human resources in organizations operating under crisis conditions: A fuzzy input-output optimization modeling framework. *Resources, Conservation and Recycling*, *128*, 250-258.
5. Bersin, J. (2017). 4 powerful AI for HR examples that show promise, minefields Retrieved June 2, 2020, from https://www.techtarget.com/searchhrsoftware/tip/4-powerful-AI-for-HR-examples-that-show-promise-minefields.
6. Bizer, C., Heese, R., Mochol, M., Oldakowski, R., Tolksdorf, R., & Eckstein, R. (2005). *The impact of semantic web technologies on job recruitment processes*. In Wirtschaftsinformatik, Physica, Heidelberg.1367-1381.
7. Bogen, M. (2019). All the ways hiring algorithms can introduce bias. *Harvard Business Review*, *6*, 2019.
8. Bondarouk, T., & Brewster, C. (2016). Conceptualizing the future of HRM and technology research. *The International Journal of Human Resource Management, 27* (21), 2652-2671.
9. Bondarouk, T., Parry, E., & Furtmueller, E. (2017). Electronic HRM: four decades of research on adoption and consequences. *International Journal of Human Resource Management, 28*(1), 98-131.
10. Bondarouk, T. V. (2014). *Orchestrating electronic HRM*. Enschede: Twente University Press.

11. Bongard, A. (2019). Automating Talent Acquisition: Smart Recruitment, Predictive Hiring Algorithms, and the Data-driven Nature of Artificial Intelligence. *Psychosociological Issues in Human Resource Management*, *7* (1), 36-41.
12. Buck, B. & Morrow, J. (2018). AI, performance management and engagement: keeping your best their best. *Strategic HR Review, 17* (5), 261-262.
13. Capelli P. (2019). Data science can't fix hiring (yet). *Harvard Business Review*. Retrieved May 15, 2020, from https://hbr.org/2019/05/recruiting#your-appro-ach- to-hiring-is-all-wrong.
14. Chang, N. (2010). *The application of neural network to the allocation of enterprise human resources*.2nd International Conference on E-business and Information System Security.
15. Charlier, R., & Kloppenburg, S. (2017). Artificial Intelligence in HR: a No-brainer. PwC. Retrieved April 10, 2018, from https://www.pwc.nl/nl/assets/documents/artificial-intelligence-in-hr-a-nobrainer.pdf.
16. Coelho, F. D., Reis, R. Q., & de Souza, C. R. (2019). *A genetic algorithm for human resource allocation in software projects*. XLV Latin American Computing Conference (CLEI).
17. Cohen, T. (2019). How to leverage artificial intelligence to meet your diversity goals. *Strategic HR Review.*
18. Connelly, C. E., Fieseler, C.,Černe, M., Giessner, S. R., & Wong, S. I. (2020). Working in the digitized economy: HRM theory & practice. *Human Resource Management Review*, *31*(1), 100762.
19. C, Barboza. (2019). Artificial Intelligence and HR. *The New Wave of Technology Journal of Advances in Social Science and Humanities 5* (4), 715 – 720.
20. Crawshaw, J., Budhwar, P., & Davis, A. (Eds.). (2020). *Human resource management: Strategic and international perspectives*. Sage.
21. Daojin, F. (2010). Notice of Retraction: Research on the comprehensive evaluation of the human resource allocation based on Analytic Hierarchy Process and Fuzzy Mathematics.*2nd International Conference on Industrial and Information Systems. (2),* 491-494. IEEE.
22. Davenport, T.H. (2019). Is HR the most Analytics driven functions, *Harvard Business Review.*
23. De Oliveira, O. J., da Silva, F. F., Juliani, F., Barbosa, L. C. F. M., & Nunhes, T. V. (2019). Bibliometric Method for Mapping the State-of-the-Art and Identifying Research Gaps and Trends in Literature: An Essential Instrument to Support the Development of Scientific Projects. *Scientometrics Recent Advances*. Intech Open.
24. Demchak, C. C. (2019). China: Determined to dominate cyberspace and AI. *Bulletin of the Atomic Scientists*, *75* (3), 99-104.
25. Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021).How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*, *133*, 285-296.
26. Ellegaard, O., & Wallin, J. A. (2015). The bibliometric analysis of scholarly production: How great is the impact? *Scientometrics*, *105* (3), 1809-1831.
27. Falletta, S. (2013). In search of HR intelligence: Evidence-based HR analytics practices in high performing companies. *People & Strategy, 36*(4), 28–38.
28. Fallucchi, F., Coladangelo, M., Giuliano, R., & William De Luca, E. (2020). Predicting employee attrition using machine learning techniques. *Computers, 9*(4), 86.
29. Gikopoulos, J. (2019). Alongside, not against balancing man with machine in the HR function. *Strategic HR Review*.
30. Guenole, N., & Feinzig, S. (2019). The Business Case for AI in HR With Insights and Tips on Getting Started. *Armonk: IBM Smarter Workforce Institute, IBM Corporation*.
31. Gulliford, F., & Dixon, A. P. (2019). AI: the HR revolution. *Strategic HR Review*.
32. Guo, W. W., & Li, T. (2020). Accounting Professional Orientation and Talent Training Based on Artificial Intelligence*. Journal of Physics: Conference Series, 1453* (1), 012066. IOP Publishing.
33. Hamouche, S. (2021). Human resource management and the COVID-19 crisis: Implications, challenges, opportunities, and future organizational directions. *Journal of Management & Organization, 1*, 1-16.
34. Heric, M. (2018). HR new digital mandate. *Digital technologies have become essential for HR to engage top talent and add value to the business*. Bain & Company. Retrieved August 13, 2019, from https://www.bain.com/insights/hrs-new-digital-mandate.
35. Hirsch B (2019). Voices and visions Tinker, Tailor, Soldier, Spy. *Journal of Business Strategy, 40* (4), 53-56.
36. HRPA. (2017). A new age of opportunities: what does artificial intelligence mean for HR professionals? Retrieved May 2, 2019, from https://www.hrpa.ca/Documents/Public/Thought-Leadership/HRPA-Report-Artificial-Intelligence-20171031.
37. Hsu, C., Kuo, H. A., Chien, J. C., Fu, W., Ma, K. T., & Chien, C. F. A (2019). Machine Learning based Intelligent Agent for Human Resource Planning in IC *Design Service Industry*.
38. Huang, L. C., Huang, K. S., Huang, H. P., & Jaw, B. S. (2004, June). Applying fuzzy neural network in human resource selection system. In *IEEE Annual Meeting of the Fuzzy Information, 2004. Processing NAFIPS'04(1)*, 169-174. IEEE.

39. Huang, L. C., Wu, P., Kuo, R. J., & Huang, H. C. (2001). A neural network modelling on human resource talent selection. *International Journal of Human Resources Development and Management, 1*(2-4), 206-219.
40. IBM (2019). How can AI innovate acceleration for HR, IBM Watson talent? Retrieved December11, 2020, from https://www.ibm.com/talent-management.
41. Ivanov, M., Ivanov, S., Terentieva, N., Maltiz, V., & Kalyuzhnaya, J. (2020). Fuzzy modeling in human resource management. In *E3S Web of Conferences 166*, 13010. EDP Sciences.
42. Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, *61* (4), 577-586.
43. Jatobá, M., Santos, J., Gutierriz, I., Moscon, D., Fernandes, P. O., & Teixeira, J. P. (2019). Evolution of artificial intelligence research in human resources. *Procedia Computer Science*, *164*,137-142.
44. Jesuthasan, R. (2017). HR's new role: rethinking and enabling digital engagement. *Strategic HR Review, 16* (2).
45. Jia, Q., Guo, Y., Li, R., Li, Y., & Chen, Y (2018). A conceptual artificial intelligence application framework in human resource management. In *Proceedings of the International Conference on Electronic Business*, 106-114.
46. Jimenez, C. C. E., Matsuzaki, K., & Gustilo, R. C. (2018). Fuzzy-based intelligent shortlisting process for human resource job recruitment procedures. *International Journal of Engineering and Technology (UAE)*, *7* (4), 229.
47. Johnson, R. D., Stone, D. L., & Lukaszewski, K. M. (2020). The benefits of eHRM and AI for talent acquisition. *Journal of Tourism Futures*.
48. Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons, 62* (1), 15-25.
49. Kaur, M., Rekha A.G & Resmi A. G. (2021). Research Landscape of Artificial Intelligence in Human Resource Management: A Bibliometric Overview. In Dev A., Sharma A., & Agrawal, S. (Eds), *Artificial Intelligence and Speech Technology,* 255-262*.* Routledge Taylor & Francis.
50. Kaur, M., Rekha A.G & Vikas S (2021). Adoption of Artificial Intelligence in Human Resource Management: A Conceptual Model. *Indian Journal of Industrial Relations 57* (2), 331-342*.*
51. Khalifa, M., & Al Baz, M. (2022). The Impact of Applying Artificial Intelligence on Human Resources Crisis Management: An Analytical Study on COVID19. *Information Sciences Letters, 11* (1), 31.
52. Khanizad, R., & Montazer, G. (2018). Optimal allocation of human resources based on operational performance of organizational units using fuzzy game theory. *Cogent Engineering*, *5*(1), 1466382.
53. Kieling, E. J., Rodrigues, F. C., Filippetto, A., & Barbosa, J. (2019). Smartalloc: A model based on Machine Learning for human resource allocation in projects. In *Proceedings of the 25th Brazillian Symposium on Multimedia and the Web*, 365-368.
54. Kiron, D. & Spindel, B. (2019). Case study: Rebooting work for a digital era. *MIT Sloan Management Review, 60*(3), 1-10.
55. Kovach, K. A., & Cathcart Jr., C. E. (1999). Human resource information systems (HRIS): Providing business with rapid data access, information exchange and strategic advantage. *Public Personnel Management, 28* (2), 275–282.
56. Küpper, D. M., Klein, K., & Völckner, F. (2019). Gamifying employer branding: An integrating framework and research propositions for a new HRM approach in the digitized economy. *Human Resource Management Review*, *31* (1).
57. Kwak, W., Shi, Y., & Jung, K. (2003). Human resource allocation in a CPA firm: a fuzzy set approach. *Review of Quantitative Finance and Accounting*, *20*(3), 277-290.
58. Leem, C. S. (1996). Personnel classification for human resource allocation-A neural network approach. *International Journal of Industrial Engineering: Theory Applications and Practice*, *3*(3), 161-172.
59. Lengnick-Hall, M. L., Neely, A. R., & Stone, C. B. (2018). Human resource management in the digital age: Big data, HR analytics and artificial intelligence. *Management and technological challenges in the digital age*, 1-30. CRC Press.
60. Leong, C. (2018). Technology & recruiting 101: how it works and where it's going. *Strategic HR Review.*
61. Li, D., Tong, T. W., & Xiao, Y. (2021). Is China Emerging as the Global Leader in AI? *Harvard Business Review*. Retrieved November 21, 2021, from https://hbr.org/2021/02/is-China-emergingas-the-global-leader-in-ai.
62. Lin, C. M., & Gen, M. (2008). Multi-criteria human resource allocation for solving multistage combinatorial optimization problems using multi-objective hybrid genetic algorithm. *Expert Systems with Applications*, *34* (4), 2480-2490.
63. Linnenluecke, M. K., Marrone, M., & Singh, A. K. (2020). Conducting systematic literature reviews and bibliometric analyses. *Australian Journal of Management*, *45*(2), 175-194.
64. Litman, D. (2016, March). Natural language processing for enhancing teaching and learning. In *Thirtieth AAAI conference on artificial intelligence*.
65. Madakam, S., Holmukhe, R. M., & Jaiswal, D. K. (2019). The future digital work force: robotic process

automation (RPA). *Journal of Information Systems and Technology Management*, 16.
66. Maity, S. (2019). Identifying opportunities for artificial intelligence in the evolution of training and development practices. *Journal of Management Development, 38* (8), 651-663.
67. Manuti, A., & De Palma, D. (2018). *Digital HR*. London: Palgrave Macmillan.
68. Markevich, A. V., & Sidorenko, V. G. (2019). Automating of Human Resources Management using Genetic Algorithms. In *2019 IEEE East-West Design & Test Symposium (EWDTS)*, 1-9.
69. Martyn, J. (1964). Bibliographic Coupling. *Journal of Documentation*, *20* (4), 236. https://doi.org/10.1108/eb026352
70. McGovern, S., Pandey, V., Gill, S., Aldrich, T., Myers, C., Desai, C., ... & Balasubramanian, V. (2018). The new age: artificial intelligence for human resource opportunities and functions. *Ey. com*.
71. Meister, J. (2019a). Ten HR Trends in The Age of Artificial Intelligence. *Forbes.* Retrieved June 17, 2020, from https://www.forbes.com/sites/ jeannemeister/2019/01/08/ten-hr-trends-in-the-age-of-artificial-intelligence/?sh=68cd6cf63219.
72. Meister, J. (2018b). The Future of Work: How Artificial Intelligence Will Transform the Employee Experience. *Forbes.* Retrieved January 30, 2019, from https://www.forbes.com/sites/jeannemeister/2017/11/09/the-future-of-work-how-artificial-intelligence-willtransform-the-employee-experience/#6737276323c9.
73. Meline, T. (2006). Selecting studies for systemic review: Inclusion and exclusion criteria. *Contemporary issues in communication science and disorders, 33* (Spring), 21-27.
74. Mentzelopoulos, M., & Economou, D. (2020). Doctoral Colloquium—A Methodology to Evaluate the Use of Serious Games in Achieving Deep Learning: An Application for Andragogy in Human Resource Development. In *2020 6th International Conference of the Immersive Learning Research Network (iLRN)*, 399-402. IEEE.
75. Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & Prisma Group. (2009). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *PLoS medicine*, *6* (7), e1000097.
76. Nawaz, D. N. (2019). Robotic process automation for recruitment process. *International Journal of Advanced Research in Engineering and Technology*, *10* (2).
77. Nicastro, D. (2020), Ways Artificial Intelligence is Reinventing Human Resources. Retrieved December 18, 2020, from https://www.cmswire.Com/digital-workplace/7-ways-artificial-intelligence-is-reinventing-human-resources.
78. Niehueser, W., & Boak, G. (2020). Introducing artificial intelligence into a human resources function. *Industrial and Commercial Training*.
79. Nocker, M., & Sena, V. (2019). Big data and human resources management: The rise of talent analytics. *Social Sciences*, *8* (10), 273.
80. Nunn, J. (2019). The Emerging Impact of AI On HR. Forbes.com. Retrieved January 26, 2020, from https://www.forbes.com/sites/forbestechcouncil/2019/02/06/the-emerging-impact-of-ai-on-hr/#501f7240549.
81. Ong, J., & Ramachandran, S. (2003). Intelligent tutoring systems: Using ai to improve training performance and roi. *Networker Newsletter, 19* (6), 1-6.
82. Pahlevan-Sharif, S., Mura, P., & Wijesinghe, S. N. (2019). A systematic review of systematic reviews in tourism. *Journal of Hospitality and Tourism Management, 39,*158-165.
83. Park, W. (2018). Artificial intelligence and human resource management: new perspectives and challenges. *Japan Institute for Labour Policy and Training, Tokyo.*
84. Parry, E., & Tyson, S. (2011). Desired goals and actual outcomes of e-HRM. *Human resource management journal, 21*(3), 335-354.
85. Priyashantha, K. G., De Alwis, A. C., & Welmilla, I. (2021). Gender stereotypes change outcomes: a systematic literature review. *Journal of Humanities and Applied Social Sciences*.
86. Qin, C., Zhu, H., Xu, T., Zhu, C., Ma, C., Chen, E., & Xiong, H. (2020). An enhanced neural network approach to person-job fit in talent recruitment. *ACM Transactions on Information Systems (TOIS)*, *38* (2), 1-33.
87. Ranjan, J., Goyal, D. P., & Ahson, S. I. (2008). Data mining techniques for better decisions in human resource management systems. *International Journal of Business Information Systems, 3* (5), 464-481.
88. Rogers, A. (2018). How is AI Humanizing People Management? *Workforce Solutions Review*, 25-26.
89. Saaty, T. L., Peniwati, K., & Shang, J. S. (2007). The analytic hierarchy process and human resource allocation: Half the story. *Mathematical and Computer Modelling, 46* (7-8), 1041-1053.
90. Schweyer, A. (2018). Predictive Analytics and Artificial Intelligence in People Management. *Incentive Research Foundation.*
91. Sheikh, S. A., Tiwari, V., & Singhal, S. (2019). Generative model chatbot for Human Resource using Deep Learning. In *2019 International Conference on Data Science and Engineering (ICDSE)*, 126-132.
92. Singh, P., & Finn, D. (2003). The effects of information technology on recruitment. *Journal of Labor Research, 24* (3), 395.

93. Sivaraman, A. (2020). Soft Side of Digital Transformation: The Connected Employee. *South Asian Journal of Human Resources Management*, *7* (1), 121-128.
94. Sivathanu, B., & Pillai, R. (2018). Smart HR 4.0–how industry 4.0 is disrupting HR. *Human Resource Management International Digest.*
95. Smith, C. (2019). An employee's best friend? How AI can boost employee engagement and performance. *Strategic HR Review, 18 (*1), 17-20.
96. Stone, D. L., Deadrick, D. L., Lukaszewski, K. M., & Johnson, R. (2015). The influence of technology on the future of human resource management. *Human Resource Management Review, 25* (2), 216–231.
97. Strohmeier, S., & Piazza, F. (2015). Artificial intelligence techniques in human resource management—a conceptual exploration. *Intelligent techniques in engineering management*, 149-172. Springer, Cham.
98. Subramanian, N., & Ramanathan, R. (2012). A review of applications of Analytic Hierarchy Process in operations management. *International Journal of Production Economics*, *138* (2), 215-241.
99. Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. *California Management Review, 61*(4), 15-42.
100. Thite, M. (Ed). (2018). *E-HRM: Digital approaches, directions & applications*. Routledge.
101. Upadhyay, A. K., & Khandelwal, K. (2018). Applying artificial intelligence: implications for recruitment. *Strategic HR Review*.
102. Upadhyay, A. K., & Khandelwal, K. (2019). Artificial intelligence-based training learning from application. *Development and Learning in Organizations: An International Journal.*
103. Van Eck, N. J., & Waltman, L. (2010). Software survey: VOS viewer, a computer program for bibliometric mapping. *Scientometrics, 84* (2), 523–538.
104. Vahdat, S. (2021). The role of IT-based technologies on the management of human resources in the COVID-19 era. *Kybernetes*.
105. Van Esch, P., & Black, J. S. (2019). Factors that influence new generation candidates to engage with and complete digital, AI-enabled recruiting. *Business Horizons*, *62* (6), 729-739.
106. Walford-Wright, G., & Scott-Jackson, W. (2018). Talent Rising; people analytics and technology driving talent acquisition strategy. *Strategic HR Review*.
107. Wang, T., & Lin, J. (2020). Research and application of practice teaching reform of HRM major under the background of AI. In *2020 International Conference on Big Data and Informatization Education (ICBDIE)*. IEEE.
108. Xu, J., Wang, B., & Min, G. (2019). Research on Human Resource Allocation Model Based on SOM Neural Network. *International Journal of Mobile Computing and Multimedia Communications (IJMCMC)*, *10* (1), 65-76.
109. Ye, Y., Zhu, H., Xu, T., Zhuang, F., Yu, R., & Xiong, H. (2019). Identifying high potential talent: A neural network based dynamic social profiling approach. In *2019 IEEE International Conference on Data Mining (ICDM)*, 718-727. IEEE.
110. Zehir, C., Karaboğa, T. & Başar, D. (2020). The Transformation of Human Resource Management and Its Impact on Overall Business Performance: Big Data Analytics and AI Technologies in Strategic HRM. In *Digital Business Strategies in Blockchain Ecosystems*, 265-279. Springer, Cham.
111. Zupic, I. & Cater, T. (2015). Bibliometric methods in management and organization. *Organizational Research Methods, 18* (3), 429-472.