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Artificial intelligence and HRM: identifying future research Agenda using systematic literature review and bibliometric analysis

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Abstract

The present research aims to identify significant contributors, recent dynamics, domains and advocates for future study directions in the arena of integration of Artificial Intelligence (AI) with Human Resource Management (HRM), in the context of various functions and practices in organizations. The paper adopted a methodology comprising of bibliometrics, network and content analysis (CA), on a sample of 344 documents extracted from the Scopus database, to identify extant research on this theme. Along with the bibliometric analysis, systematic literature review was done to propose an Artificial Intelligence and Human Resource Management Integration (AIHRMI) framework. Five clusters were recognized, and CA was conducted on the documents placed in the group of articles. It was found that vital research concentration in this arena is primarily about AI embeddedness in various HRM functions such as recruitment, selection, onboarding, training and learning, performance analysis, talent acquisition, as well as management and retention. The study proposes an AIHRMI framework developed from various studies considered in the current research. This model can provide guidance and future directions for several organizations in expansion of use of AI in HRM.

Keywords Artificial intelligence · Human resource management · Talent management · Bibliometric analysis · Systematic review

JEL Classification O15 · O33

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1 Introduction

Since the nineteenth century, AI has been viewed as an artifact of science literature; however, most professionals nowadays recognize that implementing smart technology dynamically transforms workplaces. There are applications of AI across all industries and professions, and HRM is no exception. In today's globalized world, traditional practices of conducting business are undergoing a paradigm shift. No longer are individual local companies the opponents in competition, but organizations have to compete continuously on an international level as new-fangled technologies are making the world less critical (Erixon 2018). It infers that for an organization to stay relevant and retain a competitive edge, it is key to accepting the new innovative technological advancements. As business leaders gear up for a digital world with swift impetus, AI grounded on "machine learning" technology guarantees to transform the Department of Human Resources at diverse levels (Mitchell et al. 2013). Some such levels are recruitment, training, management of career, compensation and mobility.

Artificial Intelligence also aids to attract talent with high potential and assess recommendations as rapidly as possible, investigating the appropriateness of the description, designation, and forecasting the candidate's supplementary worth for the organization, which are the foremost tasks of HR functional area (Kamaruddin et al. 2019). AI and HRM integration aim to benefit managers in accomplishing improved inter-generational association.

Even though the concept of AI has been around for a few decades, it came into the limelight after the 1950s. This was the time when the true prospects of AI technology were discovered. AI philosophy and technology implementation is also on the rise in organizations. With the help of AI, machines are able to learn with experience and accomplish human-like responsibilities. Several AI aids such as intelligent decision systems, fuzzy sets and artificial neural networks are used in several arenas (Holland 1992). Among them, AI applications in the area of HRM are still in the investigation phase (Sheila et al. 2018). In the development of HRM, usage of AI technology can fetch superior fiscal assistance since it reduces repetitive administrative tasks of HR managers by helping them: i) make decisions, and ii) predict employee behavior at work (Bersin 2018). AI technology is used mainly in recruitment, training, employee engagement and employee retention, which helps to reduce cost, save time and complete HR tasks more accurately (McDonald et al. 2017; Pillai and Sivathanu 2020).

Enhancing HRM productivity through AI technology execution has prompted an imperative inclination in future progress of this operational area. However, in research on HRM, there is still a deficiency of an inclusive AI execution framework, combined with detailed scope for HRM to examine its specific application (Nawaz and Gomes 2019; Van Esch et al. 2019; Zehir et al. 2020). This study focuses on qualitative investigation and purposes to clarify how AI has been integrated into HR's diverse functions and its influence in the focus of organizations and Human Resources. Therefore, based on different facets of HRM and technological implementations of AI, this paper offers conceptual AI applications in HRM functions to lead organizations to practice this technology, elevating HRM. The suggested AIHRMI framework imparts theoretical direction and advocates implementation for the amalgamation of HRM and AI technology. The AIHRMI framework has been designed after exploring content in this area with systematic literature review (SLR), bibliometrics and CA.

2 Literature review

This section offers the academic context of AIs in various HRM functions and practices by exploring literature. It includes areas of HRM, recruitment, selection, onboarding, training-learning, performance analysis, talent acquisition-management and retention-application of AI in various areas. Over the past years, a few scholars have completed their work efficaciously on HR analytics (Sivathanu and Pillai 2019). Researchers preferred to gather numerous studies on this topic between 1988 and 2020.

Artificial Intelligence is defined as "making a machine behave in ways that would be called intelligent if a human were so behaving" (McCarthy et al. 1955). Although AI was defined in 1955, it has gained prominence only recently due to the technological revolution across the globe. AI is discussed as non-human intelligence designed to accomplish particular activities and tasks (Dwivedi et al. 2019). Elaine Rich defines, "Artificial Intelligence is the study of how to make computers do things at which, at the moment, people are better." (Rich 1983).

HRM comprises a sequence of HR plans and consistent management actions of enterprises. These activities primarily embrace the devising of corporate HR strategies, recruitment and selection of employees, training and development, performance management, employee mobility and employee relationship management (Noe et al. 2006). Tecuci (2012) remarks that AI is widespread and multi-disciplinary. This can be utilized not only in computing disciplines but also in philosophy and linguistics. It can yield several diverse types, such as bots or software and robots (Tecuci 2012). The title of AI was bestowed in 1956 (Stuart and Norvig 2016). Salin and Winston (1992) explained that AI is a set of procedures that authorize computers to accomplish tasks that would otherwise necessitate the cognitive skills that human intelligence fetches.

According to Nilsson (2005), machines should perform the maximum of the work that human intelligence demands, calling for human-level AI. In the present competitive market full of digitization, every business person connects digitally via internet technology and gets updated on various business concerns. With the growing demand to include HR managers in tactical decisions, companies have recognized the significance of using new technology in supporting HR systems for various functions. There are several areas where AI can be executed and can occupy its place in various diverse forms. For example, it can be a robot, machine or computer program (Tecuci 2012). Some of the technological fields where AI has been extended to are robotics, natural language processing (NLP), expert systems and automated reasoning (Ved et al. 2016). In the subsequent parts of this paper, authors systematically discuss the literature of AI integration with various HRM functions as part of HR planning.

Recruitment is the first and foremost part of HRM functions in HR planning. Due to the significance HR has in any organization, the recruitment process of attaining resources is vital for its accomplishment (Kok and Uhlaner 2001). Before implementation of AI, recruitment process used to be lengthy; it took a considerable amount of time and paperwork. Gradually, a common practice has been to replace it with online recruitment (O'Donovan 2019). Studies are generally keeping pace with how this process can be upgraded with technological support (Galanaki et al. 2019). Currently, a lot of attention is focussed on further technical developments to serve recruiters. The procedure is becoming more automatic as human involvement is reduced (Bondarouk and Brewster 2016). In an article, Baxter (2018) tries to foresee the tendencies to take over the recruitment process. He advocates analytics to take away some of the estimations, but he, too, suggests AI as a device that can be applied when interview is conducted (Baxter 2018). Still, it remains challenging to recruit the most competent and best employees in the market due to extensive competition in the job market (O'Donovan 2019).

Upadhyay and Khandelwal (2018) present AI-driven recruitment assistant chatbots that permit candidates to be connected personally and receive information via text messages or a dialogue box. Several computer-aided tools assist in matching aspirants to a job, which help to reduce recruiters' workload. Such methods include software that uses learning-based techniques and algorithms to resume and implement the matching process (Montuschi et al. 2013).

Another remarkable facet of AI-based classifications is the possibility of collecting information about candidates' personality characteristics, which are highly critical in filling job vacancies. These attributes are frequently observed during work interviews; however, initial data can be gathered via searching websites. Interviews related to employment, supplemented by a video interview, are becoming a popular way for companies to recruit. HireVue has developed video interview applications that employ AI. AI is skilled in reading and evaluating applicant's body language, facial expressions, or tone of voice. Hilton's global hotel chain recognized several advantages in conducting video interviews; the most outstanding implication observed was reduction in the time taken for recruitment. Earlier, it took 42 days for the Hilton hotel recruitment process, but now it takes only five days due to the use of AI-based video interviews (HireVue 2017; Suen et al. 2020).

Further, after selecting or positioning candidates, AI also plays a role in onboarding new starters. It is especially important for providing details to new employees relating to their working lives. It offers a centralized point for accessing the type of information that each new starter needs, reducing uncertainty and making the staff less likely to feel exhausted (Randstad 2020).

While embarking on a development phase, both internal and external impacts keep employees pushing forward. Using a diverse range of AI technologies helps companies form a learning culture within the organization that can be comprehensive, avoiding the usual model of teaching design rooted in the model's ability for conventional gap analysis. In the present situation, enterprise training can identify the workforce who are required to learn in a particular situation, from the massive knowledge base through big data analysis. This can further help form an individualized member curriculum, thoroughly measure and identify personnel level through new technologies, and constructively encourage customized courses.

After training and learning, a performance assessment model can be incorporated into the program by gathering and reviewing information relating to employees' job performance. Some experimental evaluation techniques, such as 360-degree performance appraisal approaches, can be used more efficiently and progressively using the intelligent decision support system (IDSS) (Otley 1999; Góes and De Oliveira 2020). Such forms of assessment are developed and inserted into the decision support system to measure outcomes of the evaluation of employees more effectively.

During the hiring process, measures such as information tests, cognitive tests, personality tests, reference checks, structured/unstructured interviews, work samples. Such functions can be applied with sophistication and in time, knowing that who can perform best in the appropriate job position (Mahmoud et al. 2019). Decision-makers can evaluate an indicator's relevance using AI and point out flaws of ineffective standards. They can also articulate and enforce new pragmatic indicators and recommend improvement plans.

Besides, AI is used to understand workers' emotions by analyzing their experiences in organizational environments such as intranet, email etc. Employee's Voice (VoE) has the ability to infer a person's interests, opinions and well-being. AI-led virtual supporters in text and voice can also help HR practitioners give better attrition forecasts, improve accessibility and other workplace-related outcomes.

The earlier-discussed HRM function of performance appraisal will further help managers in talent acquisition. The application of AI for talent acquisition in companies help to achieve numerous outcomes such as advanced ability to recognize aspirants with: (i) the required abilities, (ii) employ less time scrutinizing resumes, (iii) fill open positions faster, (iv) improve candidate understanding, (v) lessen undesirable hires, (vi) classify superlative internal entrants, and (vii) intensify assortment of new employees (Oracle 2019). Successful implementation of talent acquisition can be verified with the help of attrition. Although turnover, at a steady pace, may be attractive as it may allow the firm to: (i) inject young faces, (ii) lessen employee costs and reconstruct culture, and (iii) it becomes a severe issue beyond a point because it depletes the company's cream i.e., talented and experienced employees of the organization. In a competitive employment market system, organizations cannot handle high attrition, especially with regards to their best talent.

> "The key to [the] effective use of AI for retention is combining big data and machine learning with the human touch. Any company that decides to use AI to retain better talent and develop its workforce should ensure they have an HR team that understands the balance between relying on technology and the inherent nuances of working with people. New applications of artificial intelligence (AI) in HR may hold the key to reducing employee turnover for good." (Beg 2019)

Mallick (2019), in an exclusive interview with Sanja Licina, PhD in "How AI identifies to fight risk and helps retain high-value employees, *Future of*

Organisations at Globant, explained the role of AI in retaining employees. Licina explains that AI is applied to combine and categorize member exchanges and engagements via a common stage, offering executives an understanding of changing aspects of the organization. Licina also discussed that by specialist care and employees' daily connections with their peers, organizations could influence AI to classify these occurrences and evaluate patterns to regulate staff dedication.

All the above discussed arenas are further connected to the automation of HRM functions.AI in HR saves time by automating tedious, low-value-add activities, allowing HR to concentrate more on strategic, value-added tasks such as mentoring and continuous feedback. Time-consuming tasks such as scanning resumes, scheduling interviews and selecting a candidate, can be done quickly and efficiently with the assistance of AI-driven HR solutions. By reducing the administrative burden, HR employees can tackle more purposeful and challenging tasks, increasing their level of motivation and engagement. Automation reduces the risk of human error and ensures that employee data is adequately safeguarded (StarMeUp 2018). Thus, this section has included an extensive discussion on all previous research in this area. The intensive literature study has helped draw Fig. 1, which provides information regarding AI techniques and the evolution of HRM functions over the past couple of decades.

Figure 1 also depicts that AI and HRM have been widely discussed areas in recent years. It can be concluded from studies discussed earlier that researchers have concentrated on some specific functions of HRM for integration with AI. However, significantly fewer studies are available, focussing on the framework of HRM functions, AI, and other related technologies (Duchessi et al. 1993; Liang and Liu 2018; Jia et al. 2018). In their study, Duchessi et al. (1993) discussed a simple

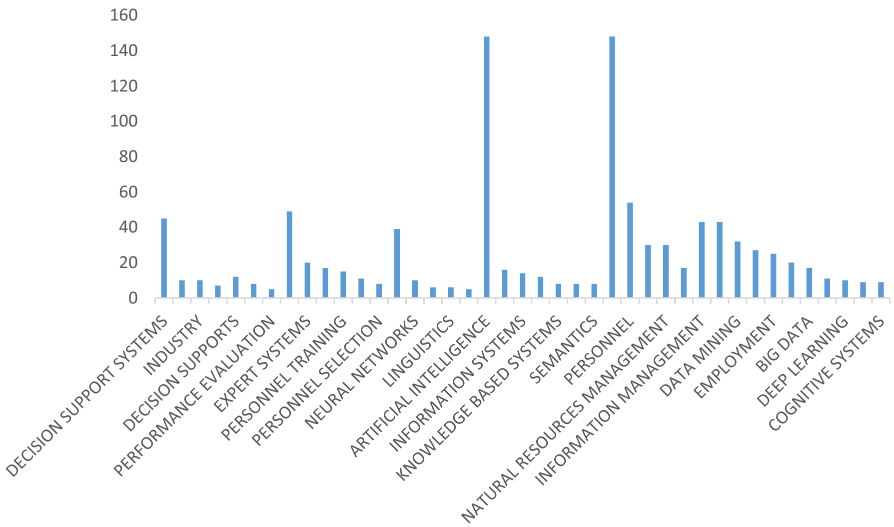

Fig. 1 Topic trend over the period (*Source*: Authors)

framework dealing with the interaction of various variables like AI, management and organizations.

Liang and Liu (2018) reviewed academic literature associated with the "Big Data" and "Business Intelligence" (BI) model, and Jia et al. (2018) proposed a conceptual AI framework for HRM, based on the six dimensions of HRM and status quo of AI technologies. Therefore, based on future directions as proposed by these aforesaid studies discussing previous AI and HRM function-based concepts, the researchers aimed to develop a comprehensive framework to overcome from the limitations of these studies.

After viewing gaps in the earlier-discussed contexts, researchers-initiated discussion on various concerns such as bibliometric, SLR, CA, integrated AI and HRM models, for the current study.

2.1 Rationale for the study

Human Resources has been undergoing a primary revolution with AI's assistance, which has been gradually impacting several HR operations. These functions, completely carried out by humans earlier, are restructured with the help of a computer-generated assistant. HR functions such as performance appraisal, learning and development, and talent acquisition are a few of the areas where AI has been introduced.

While investigating studies related to AI and HRM trend analysis, only one paper was found briefing a survey on such integration, its related literature, and directions for future fact-finding. Berhil et al. (2020), in their research, primarily summarized AI in the service of HRM, from sizeable national and international literature. The present study focuses on the integration of AI in various HRM functions. Unlike prior analysis, the research methodology used in this study is an amalgamation of bibliometrics, network analysis (NA), and SLR. Which enabled recognition of the intellectual structure and compilation of a comprehensive summary of the study area. Moreover, there are several other substantial variances among our analysis and Berhil et al. (2020), as shown in Table 1.

Table 1 offered an improved relative consideration of the similarity and variances between the present research work and Berhil et al. (2020). So, to overcome the differences found in the mentioned study, the following objectives were addressed for AI and HRM:

1. To study the intellectual structure of research in this field;
2. To study the common theme of research widely embraced by researchers.

In response to the issues specified earlier, researchers have used the bibliometrics approach. It is the complete appropriate process for reviewing the theoretical formation of an investigation arena (Castriotta et al. 2019; Block and Fisch 2020). Therefore, the current study presents the method and various subparts of descriptive analysis (Fig. 2). It also comprises the CA followed by KA.

Table 1 Comparative analysis of previous and present studies

Criteria	Berhil et al. (2020)	Present study
Keywords	Exclusion of keyword-based search	Comprehensive searching of "artificial intelligence" AND "HRM"
Database	No database involved in search of documents	The database of Scopus was used for outlining better and clear guidance to future researchers
Focus	The study proposes that HR scholars face problems for which computer engineers pursue resolutions. At the same time, it summarises the current and specific techniques and IT methods and technologies now employed by highlighting those using AI during the period 2008 and 2018	The focus of this research is to identify the relationship and integration of AI and HRM Further, a comprehensive SLR, bibliometric analysis, and CA were also used to decipher the integration and recommendations for future research
Methodology	In this study, the researchers have started with an extensive review of different HR problems and risks reported by HR specialists. Then a comprehensive review of recent research efforts on computer science techniques was proposed to solve these problems, and finally, focussed on suggested AI methods. The period chosen for the research was between 2008 and 2018, and majority of the articles were published in newspapers	Extensive search of AI and HRM and related trend analysis discussion with the inclusion of SLR, bibliometric, network, content, CoC, and cluster analysis was performed
Findings	The HR issues discussed in the study were about evaluating and envisaging: recruitment, skills management, HRD, attritions, and turnover The paper highlighted major technologies such as data mining, BI, and big data The AI algorithms used in the study were related to support vector machine, decision tree, and random forest	Significant results—topmost contributing publisher, journal, author, affiliated institution, geographical regions, most cited and co-cited documents, CoC network, cluster identification, the thematic flow of knowledge, and keyword analysis (KA)

Table 1 (continued)

Criteria	Berhil et al. (2020)	Present study
Gaps identified by researcher and future directions	The researcher claimed that the study imparted knowledge of existing technologies and algorithms combined with HR analysis and HR approaches. So, a requirement for further expansion and progress from a theoretical or real research material perspective was suggested There was discussion only of limited HRM functions The period was limited to 10 years only. However, the domain has advanced in a lot of ways This study focused on presenting the issues that HR researchers face and for which computer scientists seek solutions	Gaps given below have been identified in the current study, which can be discussed in future studies: AI-based HR applications have robust potential to elevate staff efficiency and support HR professionals to become knowledgeable consultants to improve employee performance. But in current literature, very little research is found for more significant HRM functions in AI and HRM, such as cross-cultural management, industrial relation, and compensation management Technological revolution and speedier pace of internationalization leads to a more strategic part for HRM, as a key element of accomplishment or failure in cross-border business. In the summarized section of the current study, "gaps identified in the current literature study" portrays lack of cross-border collaboration of HRM and AI. So, undertaking cross-national comparative research in the future will inform practice on making strategic international decisions of whether and when to implement AI and HRM integration Various studies from current literature depicted that researchers' have discussed a particular sector only. Thus, there is less availability of cross-sector collaboration studies. So, the gap presented through existing literature can be discussed by future researches with the association of two or more sectors like healthcare and IT, IT and hospitality etc

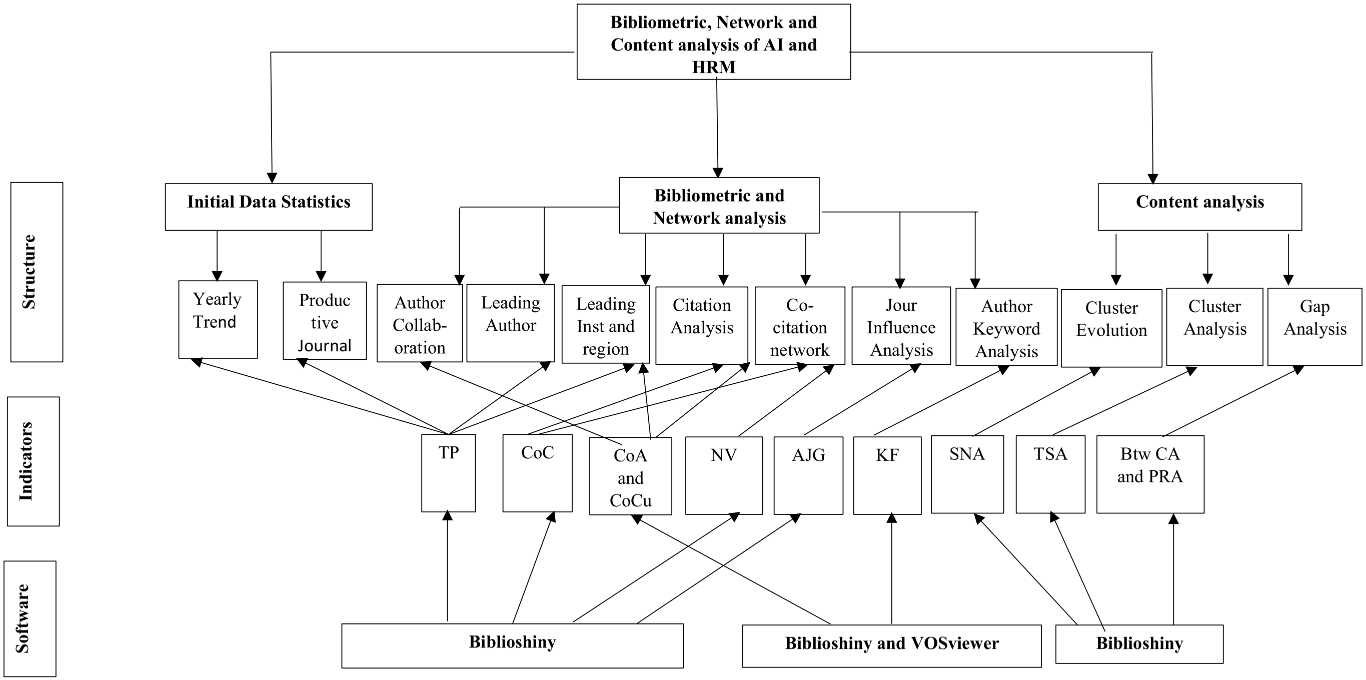

Fig. 2 Systematic structure of study (*Source*: Authors). *Note* TP = Total publications, CoC = Co-citation count, CoA = Co-authorship, CoCu = Collaboration of countries, KF = Author key-word frequency, AJG = Academic journal guide, SNA = Social network analysis, NV = Network visualization, BtwCA = Between centrality analysis, PRA = Page rank analysis, TSA = Thematic structure analysis

3 Methodology

For studying the literature on AI and HRM in the context of various organizations, bibliometric analysis has been applied with the assistance of tools like citation, co-citation count (CoC), keyword, and co-authorship (Xu et al. 2018; Cisneros et al. 2018). Co-citation is defined as the frequency with which two documents are cited together by other documents (Small 1973). The more co-citations two documents receive, the higher their co-citation strength, and the more likely they are semantically related. In the KA, by counting the appearance frequency of keywords, hotspots of disciplines can be analyzed (Huai and Chai 2016). Co-authorship is a common practice in the field; hence, multiple-author papers were chosen as an indicator of collaborative activity within a field (Newman 2001, 2004; Melin and Persson 1996; Katz and Martin 1997; Wagner and Leydesdorff 2005).

The idea is that co-authorship is one of the most tangible and well-documented forms of scientific collaboration and the output of these interactions creates a "co-authorship network" (Newman 2001; Glänzel and Schubert 2004). Thus, a combination of CoC (semantic relationship of documents), KA (hot disciplines), and co-authorship analysis (collaborations within a field), helps to know the most prevalent areas in this field. Thus, the current study is NA, along with an amalgamation of SLR (Fisch and Block 2018), bibliometric, and CA. This paper uses the *Biblioshiny* application, developed on the R language and VOSviewer. Researchers used this application because it provides a web interface, secure data importing, conversion, gathering, and filtering data from collection frames like Scopus.

In contrast to the trial-and-error method, the aim of an SLR is to thoroughly pursue and discover studies to complete an analytical assessment of literature to find potential research gaps (Tranfield et al. 2003). For a wide-ranging systematic review of literature, three foremost steps were measured: (i) data collection,

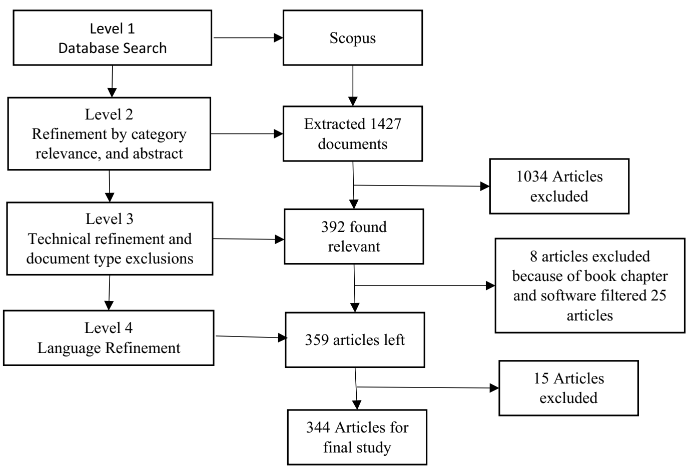

Fig. 3 Procedure of delineating articles (*Source*: Authors)

which consists of data loading and converting, (ii) analysis including descriptive and network matrix creation (bibliographic coupling, co-citation, collaboration, and co-occurrence analysis), and (iii) visualization provides mapping of the results. Relevant papers cited throughout SLR were taken to accomplish bibliometric and content summaries. The bibliometric analysis used a well-defined protocol, which begins by defining a topic of intellectual interest and then follows three sequential steps to provide directions for advancing research on the topic in future (Fig. 3). For an improved consideration, the procedure used in this study's systematic structure is shown in Fig. 2.

3.1 Defining the appropriate terms for search

The theme of AI and HRM has been discussed in the current paper with various transformative functions of HRM in integration with AI. To ensure that this keyword includes all the terms, researchers searched a string with its related keywords. The final search string for document search included TITLE-ABS-KEY ("Human resource management" OR "HRM" and "Artificial Intelligence" OR "AI"). Earlier literature analyses in the same area was deliberated to categorize related keywords exploration. The search strings were validated by their ability to detect several known primary studies.

A prior search was conducted using a set of broad search terms, and many relevant publications were identified. The list of publications identified by Legris et al. (2003) was used to validate the search string before undertaking the review.

3.2 Refinement of search results

Early probe was tracked on the Scopus database on 27 May 2020, with the established search string. After going through the entire subject on the databases mentioned earlier, researchers first located 1,427 documents. The final specified quantitative figure of 344 documents results from the amalgamation of elimination and insertion principles. Hereafter, researchers followed four steps to classify the most appropriate papers for the concluding assessment (Fig. 3). Document types for the current study include articles, documents in the press, conference papers and review articles.

From 344 documents, researchers identified papers related to business management and accounting, economics, computer science, engineering, social sciences and several other significant areas. Documents emerging from the search keywords were checked with the help of abstract reading to make the study more extensive. Next, articles that were not relevant to the current arena were omitted. Further, documents other than in the English language were also excluded from the study. Finally, 344 documents were found suitable to proceed with the analysis.

3.3 Initial data statistics

As seen in Fig. 2, 344 articles supported continuing publication inclination on this theme. The evaluation was done considering publication based on the year, region, country, journal and institution.

4 The trend of publication (yearly basis)

Figure 4 indicates the year-wise distribution of research publications during the period under study. The maximum number of publications increased during 2018 and doubled in 2019, i.e., 45 and 95 respectively. The rising inclination to include AI in various HRM functions is the outcome of digital transformation technologies, bringing new challenges to HRM and helping employees and organizations to adapt to changes. Moreover, AI-powered technology is proving itself to be an effective solution to address HR pain points. It has already begun to generate results. As more and more solutions emerge, it is clear that digital HR practices are a reality that will continue to evolve and spread.

5 Most productive journals

The list of ten most productive journals contributing at least two articles in this area is given in Table 2. It can be seen from Table 2 that *Advances in Intelligent Systems and Computing* contributed maximum articles i.e., 21 with Journal Impact Factor (JIF) 0.57, published from Springer Science and Business Media, followed by *Communications in Computer and Information Science* with six articles having JIF 0.49, published from Springer Verlag.

5.1 Bibliometric analysis

This method is commonly applied to information and library science etc., but has current validity in social-science research. It utilizes publication databases to construct operational metaphors of logical arenas through bibliography data (Zupic and Čater 2015). Based on association indicators, it is typically divided into two forms. The first part concentrates on facts concerning the measure of the impact factor; the second recognizes the interconnected relatives amongst several

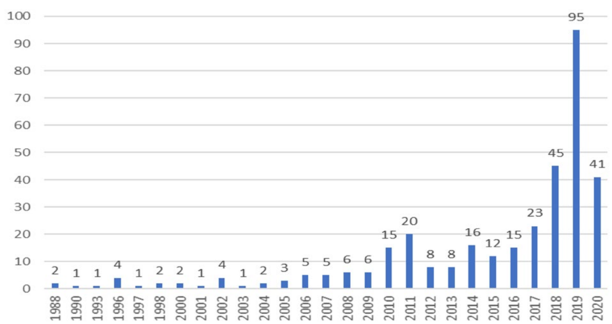

Fig. 4 Yearly publication of articles published on AI and HRM (*Source*: Authors)

Table 2 Top contributing journals (*Source*: Authors)

S. No	Sources	Publication name	JIF	Articles
1	Advances in Intelligent Systems and Computing	Springer Science + Business Media	0.570	21
2	Communications in Computer and Information Science	Springer Verlag	0.490	6
3	Expert Systems with Applications	Pergamon-Elsevier Science Ltd	5.890	5
4	Frontiers in Artificial Intelligence and Applications	IOS Press	0.470	5
5	International Journal of Recent Technology and Engineering	IJRTE	1.0	5
6	International Journal of Scientific and Technology Research	IJSTR Publications	0.787	5
7	Computers in Human Behavior	Elsevier	5.880	3
8	International Journal of Advanced Science and Technology	Science and Engineering Research Support Society	0.410/0.410	3
9	Procedia Computer Science	Elsevier	1.26	3
10	Boletin Tecnico/Technical Bulletin	Centro de Estudios del Desarrollo de la Universidad Central de Venezuela	0.080	2

Clarivate Web of Science Journal Citation Reports, 2019 study areas as well as among scholars. Both actions affect the comprehensive evaluation of the content of investigation and its advancement (Ramos Rodríguez and Ruíz Navarro 2004). Citation and CoC analysis are the most used extensive methods to gain such outcomes.

5.2 Affiliation analysis

This section discusses the top ten institutions that produced the highest research outputs on AI and HRM during the period under study. These institutions together contributed 114 articles. The Federal University, IBM India Research Laboratory and the National University of Defence Technology have contributed the same number of articles, i.e., nine, followed by Universiti Teknologi Mara, the University of Milan-Bicocca and Vilnius Gediminas Technical University, with eight articles each. On the other hand, four affiliations, namely, Daffodil International University, Northwest University, Saarland University and Universitas Prima Indonesia, contributed the same number of articles, i.e., seven documents.

Research on AI and HRM contributions of the top ten countries during the study have shown that India, with a share of 125 articles, is in the third position in research output after China and the US, 147 and 145 respectively. The next most contributing countries are Italy (45), UK (31), Germany (29), Australia (27), Spain (27), Malaysia (24), and Brazil (22). It was also disclosed that China, the US, and India have the maximum partnership strength with other countries.

Further, it has also been found from analysis of the most influential regions, extracted with the help of bibliometric analysis, that the current alluring trends of AI are attracting all industries across different countries. Developed, developing, and under-developed countries are all focusing on AI adoption for better futuristic opportunities and development. While AI technology is flourishing worldwide, some major AI powers are working hard to win the race. In the list of top ten countries leading the AI rush across the globe, China has always displayed significantly high ambitions for becoming the AI "superpower of the world." In the light of this goal, the State Council of the People's Republic of China has announced plans to become a $150 billion AI global leader by 2030 (Srivastava 2019).

The goal is not vague but looks achievable as China is already a global leader in AI research. Moreover, the country has published several research papers on deep learning, comparatively more than other leading countries. The biggest aiding factor is its population using the internet (approximately 750 million people), generating a huge digital data supply for processing. The US gives tough competition to China in terms of becoming an AI superpower. With the well-established technical culture in the US, the country has benefited with $10 billion in the channelling of venture capital in the area of AI.

5.3 Author impact analysis

The list of ten top authors who are the highest contributors to research output on AI and HRM, and the complete publication of these top productive authors during the period under study, are listed in "Appendix". Out of the ten authors, five are from China, one is from the Russian Federation, three from Malaysia, and one from Germany.

Researchers formerly observed significant contributors who combined in more than one document to identify the shared aims of authors' partnerships. It is the most prescribed technique of academic interrelation in systematic research (Cisneros et al. 2018; Acedo et al. 2006). This study was also completed through the assistance of Biblioshiny. It is found that there are many well-built co-author associations like Liu J and Wang T, who have four publications in association with one another ("Appendix").

5.4 Journal impact analysis

Researchers' studies journal's impact in two parts. They studied total citations of the papers of the leading journals in this area and adopted the *Academic Journal Guide* (AJG) rating. Total number of documents published is an assessment of the journal's effectiveness; however, citation count is an assessment of the journal's impact (Svensson 2010). Consequently, to examine the top significant journals, researchers considered total citation of the articles of the top ten journals in this study area ("Appendix"). It is seen that journals that attained a leading figure for publication also have a higher frequency of citations. But it was proved wrong for *Advances in Intelligent Systems and Computing,* which has total citations (11) with 21 documents. Moreover, *Expert Systems with Applications* has 132 citations with only five articles.

5.5 Journal quality analysis

The top ten journals preferred for publications on AI and HRM, which have AJG 2018 ratings, are discussed in this section. The AJG 2018 rating was considered to assess the quality of journals. Four journals with three AJG 2018 ratings each were *Expert Systems with Applications*, *Computers in Human Behaviour*, *Procedia Computer Science*, and *Boletin Tecnico/Technical Bulletin,* followed by the *International Journal of Scientific and Technology Research* having two AJG 2018 ratings.

5.6 Citation analysis

Citation analysis was performed through analysis of citation, centrality, closeness and page rank analysis. Citation reflects an association between the cited and citing articles. It reports the number of times other publications cite a given article to determine the influence on the scientific community and the effect of the article (Ding and Cronin 2011).

5.7 Co-citation analysis

Co-citation analysis is undertaken when two writers or sources are seen in conjunction with the reference list of a sole publication (Tunger and Eulerich 2018). Thus, the CoC examination is a device to estimate the relative comparison of numerous publications accompanying a related subject, model, procedure or experimental discipline (Small 1980; Gmür 2003).On evaluating CoC using VOS viewer, the researchers analyzed 32 pairs of authors, who are co-cited with each other at least three times. Table 3 discloses that Huselid (1995) has the highest count of CoC, with co-authors; Aral et al. (2012); Becker and Gerhart (1996); Stone et al. (2015); Angrave et al. (2016); and Marler and Boudreau (2017).

5.8 Co-citation networking and clustering evolution analysis

This analysis helps to distinguish the IS of the paper. The researchers considered clusters from the CoC network and supported a CA to differentiate the IS of the theme "AI and HRM." To design a CoC network, researchers typically began by choosing a set of cited papers and then computing all the co-citations between each document pair (Small 2009).

A co-citation network is consequently a completed set of edges and nodes; nodes characterize the stated papers, while edges represent the associations that depict co-occurrence of nodes (Leydesdorff 2015). In the present paper, CoC analysis has been accomplished with the help of Biblioshiny. Applying Biblioshiny to structure clusters enhances recognising the source on which the software configures groupings.

Table 3 Article coupling with maximum CoC (*Source*: Authors)

Sr. No	Paper	Count of co-citations (Local and Global)
1	Huselid (1995)	7
2	Mehrabad and Brojeny, M.F. (2007)	7
3	Breiman, L., Random Forests (2001)	6
4	Haines and Petit (1997)	5
5	Chien and Chen (2008)	5
6	Aral et al. (2012)	4
7	Becker and Gerhart (1996)	4
8	Stone et al. (2015)	4
9	Ball, K.S. (2001)	4
10	Hendrickson, A.R. (2003)	4
11	Angrave et al. (2016)	4
12	Marler and Boudreau (2017)	4
13	Ajit, P. (2016)	4

The default procedure of cluster emergence with this software is the algorithm of Louvain. The Louvain method of community detection was proposed by authors from Louvain University in 2008 and aimed to draw communities from an extensive network. It works on determining the optimal number of partitions which maximizes the Modularity Index (Blondel et al. 2008). Modularity can be explained as a value between − 1 and + 1 that computes the density of links (edges) inside groups compared with connections among groups. With the CoC connections of the 344-representative set, Biblioshiny software evolved six clusters by applying this process. Popularity and prestige are two different measurements of the impact of a paper. A seminal paper (citation measure) might not be a highly prestigious paper (PageRank measure). Prestige is an important measure of impact (Ding et al. 2009). PageRank can measure both popularity and prestige of a paper (Brin and Page 1998).

In the present study, for more validation of results, clustering of famous papers has been finalized based on the Btw (Between) centrality (a metric used for measuring the number of shortest paths that passes through the target node), closeness (measures average farness to all other nodes) and PageRank (structural relationships between nodes). All three bases have been taken for the study because it leads to more authentication. Consequently, the researchers have acknowledged the first five papers from each group with the support of their earlier-discussed metrics to confirm extremely vital documents in cluster evaluation.

Table 3 depicts the top 25 articles in the five clusters. Researchers have preferred to demonstrate the CoC network of five top papers within an individual

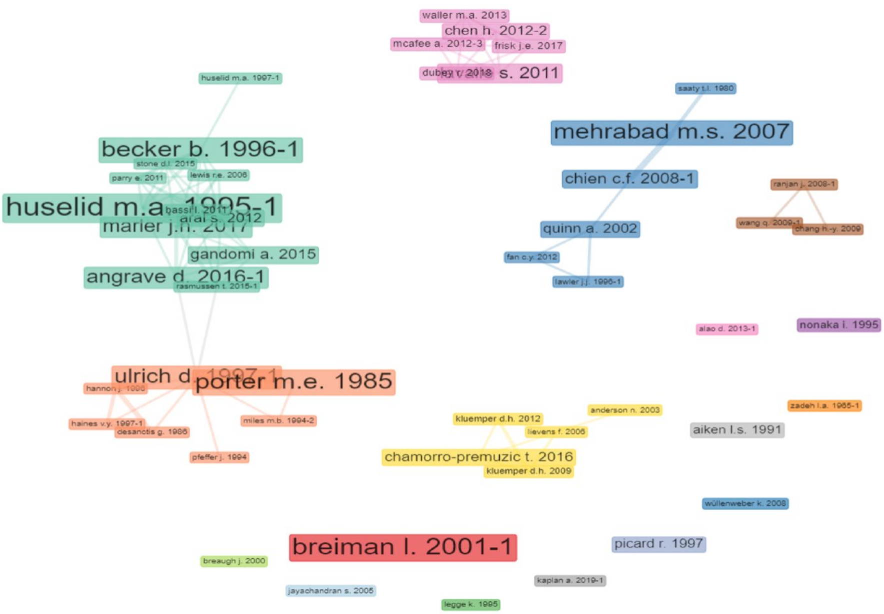

Fig. 5 Co-citation network of lead papers (*Source*: Authors)

cluster in place of whole documents for superior considerate and systematic productivity. In Fig. 5, nodes characterize the co-cited articles and edges (lines) among the nodes embody solidity within documents. Nodes associated with a similar cluster carry similar colour.

6 Clusters for content analysis

The thrust of this part is to determine the beginning and growth of all research sub-themes in arenas such as AI, its various related technologies, and integration with different functions of HRM in organizations. Researchers have piloted content evaluation for all the five clusters obtained from CoC analysis to categorise the knowledgeable research structure on AI and HRM. Table 4 gives details of all these clusters.

6.1 Cluster I: human resource analytics effectiveness

This cluster started evolving in 1996. Current elements of the cluster discussed various areas of HR analytics such as its effectiveness, potentialities, transformative role and related benefits. For structural effect, Marler and Boudreau (2017) discussed three moderators (right knowledge and skills, supportive stakeholders and IT-enabled HR analytics). Further, the researchers also mentioned that HR analytics effectiveness could be proved by concentrating on formal HR procedures such as staffing, performance management, talent, training and development, instead of endeavouring to research implementation and effect around the scope of HRM practices. Aral et al. (2012) tested for three-way variables, i.e., information technology (IT), HR analytics and performance pay practices efficacy.

The study revealed that such three-way counterparts produce excessively greater benefits than pairwise relationships. Bassi (2011) established in their study that an additional side-benefit of HR analytics would assist in finding where initiative, resources and finances do not generate their intended impacts and the workflow while increasing HR performance. Angrave et al. (2016) discussed the transformative role of HR as analytics. They highlighted that the HR world is abuzz discussing big data and the revolutionary potential of HR analytics. Experts have summarized that HR analytics must remain proficient in ensuring its future as a strategic management tool while improving organizational efficiency (Pillai and Sivathanu 2021). This cluster mainly focuses on the HR analytics significance in HRM. Hence, it will benefit if the discussion on Human Resource Information Systems (HRIS) is included in this content. The next cluster discusses various themes related to HRIS to overcome the limitation of this cluster.

6.2 Cluster II: human resource information systems

This cluster has developed consistently since 1985 with the central theme of the HRIS. Desanctis (1986) has discussed that organizations are always profoundly

Table 4 Top 5 papers in clusters using btw centrality, Closeness and Page Rank criteria (*Source*: Authors)

Author	Btw Centrality	Closeness	PageRank	Author	Btw Centrality	Closeness	Page Rank
Cluster-I				*Cluster-II*			
Marler J.H. 2017	18.7757	0.000632	0.039087	Ulrich D. 1997–1	83	0.000631	0.042685
Aral S. 2012	13.15602	0.000632	0.036148	Desanctis G. 1986	0	0.000625	0.024563
Bassi L. 2011	13.15602	0.000632	0.036148	Hannon J. 1996	0	0.000625	0.024563
Becker B. 1996–1	17	0.000629	0.031487	Haines V.Y. 1997–1	0	0.000625	0.022145
Angrave D. 2016–1	41.59779	0.000633	0.027206	Porter M.E. 1985	0	0.000625	0.014305
Cluster-III				*Cluster-IV*			
Mehrabad M.S. 2007	4	0.000452	0.034246	Lavalle S. 2011	0	0.000454	0.0246
Chien C.F. 2008–1	6	0.000453	0.02988	Chen H. 2012–2	0	0.000454	0.0246
Quinn A. 2002	6	0.000453	0.028222	Dubey R. 2018	0	0.000454	0.0246
Fan C.Y. 2012	0	0.000452	0.020324	Frisk J.E. 2017	0	0.000454	0.0246
Lawler J.J. 1996–1	0	0.000452	0.020324	Mcafee A. 2012–3	0	0.000454	0.0246
Cluster-V							
Lievens F. 2006	3	0.000444	0.033019				
Kluemper D.H. 2009	0	0.000443	0.027585				
Kluemper D.H. 2012	0	0.000443	0.027585				
Chamorro-Premuzic T. 2016	0	0.000443	0.024105				
Anderson N. 2003	0	0.000443	0.010707				

concerned in offering resources for enriching the management of HRIS. However, to accomplish "success", all issues concerning the development and operation of this system should be resolved; moreover, views of personnel management, management information system (MIS), and top management should be coordinated. It has been further discussed by Hannon et al. (1996) that a balance between global integration and local responsiveness should be made by maintaining operational issues and strategic considerations, to strike for the overall effectiveness of an organization in the context of HRIS.

Haines and Petit (1997), in conjunction with the researchers' earlier findings, revealed that the HRIS model is a critical requirement for any organization and forms the basis for planning, designing and implementing successful systems.

6.3 Cluster III: human resource functions

It is the most significant cluster as the available documents discussed various HRM functions and their inclusion in varied AI techniques. Mehrabad and Brojeny (2007) concluded that the use of intelligent and structured approaches in an organization's HRM and personnel processes has a significant impact on organizational evolution.

They further elaborated on some of the most imperative personnel operations of the company, which can use the expert system: decision-making regarding the best applicant for a job with reference to organizational characteristics, job rotation system and training terms. They have also explained decision-making about the employee's place of work with respect to psychological conditions and organizational environment, job description, calculation and determination of salary parameters of working staff, and building an image of the working environment and future of their profession. Chien and Chen (2008) study focused on bridging the gap in HR by establishing a decision tree resulting from a data mining system and associated rules to engender suitable staff selection rules.

Results provided decision rules concerning employee data with the performance of work and retention. Quinn et al. (2002) explained that numerous quantitative techniques, such as logistic regression and a neural network, assisted human service managers in foreseeing employee retention and help them develop a turnover model. Fan et al. (2012) elaborated on the use of cluster evolution for data mining and machine learning, to forecast patterns in employee turnover rates in technology, including hybrid artificial neural networks and the self-organizing map clustering study. Lawler and Elliot (1996) explained that expert systems help achieve performance and psychological outcomes for an organization. Thus, it has been concluded from this cluster discussion that various AI technologies have a significant impact on HRM functions.

6.4 Cluster IV: big data

The current cluster discusses big data. In their study, Lavalle et al. (2011) discussed how intelligent organizations employ analytics to convert information into understanding and act. Organizations believe that analytics offers value. They prioritize improving information, analytics, the pressure to adopt advanced information, analytics approaches, and innovating to achieve competitive differentiation. Chen et al. (2012) discussed big data's impact on BI and analytics, and offered a structure that described BI evolution, applications and growing research areas. Dubey et al. (2019) examined when and how establishments build big data analytics ability to advance supply chain agility and acquire competitive benefits. Frisk and Bannister (2017) discussed about growing digital technologies continuing to employ innovative ways to accumulate and explore information.

Some academics have concluded that skilful usage of data analytics and big data can help completely recover organization's productivity. Managers are required to change their decision-making philosophy and upsurge the degree of association to accomplish such enhancements. Mcafee et al. (2012) elaborated on big data as the uprising of management and said, "You can't manage what you don't measure." There is much wisdom in this saying, highlighting why the current explosion of digital information is so imperative. Simply put, because of big data, supervisors can measure, and hereafter identify their businesses completely, and directly interpret that knowledge for enhanced decision-making and performance.

6.5 Cluster V: artificial intelligence application in human resource functions

Cluster V discussed the various selection techniques used with the integration of AI and HRM. In their study, Lievens and Sackett (2006) examined situational judgment tests (SJTs), which are video-based and have sophisticated analytical sound compared to written SJTs. Kluemper and Rosen (2009) explained the use of social networking websites (SNWs) such as MySpace and Facebook, which has become prevalent, mainly with today's new personnel. The research also particularized that managers, conscious of this situation, have initiated the practice of evaluating individual data existing on SNWs to make employment choices. Kluemper et al., (2012) focused on SNWs and the less time-consuming nature of personality screening through SNWs. Normally, the profile valuation in social networking took 5 to 10 min; moreover, it did not involve the respondent's presence. The study discussed the negative impact of this method, mentioning that the candidate's data used in the appointment decision could be challenging and thus weaken the probable advantages of SNW evaluation.

Chamorro-Premuzic et al. (2016) suggested using in-house data as another source of talent acquisition information. It is a digital world, and much work is now documented electronically and transferred across the internet. Anderson (2003) presented a narrative analysis of candidate and hiring manager study responses to emerging technology such as telephone and video-based interviews, and behavioral decision testing for employee selection. Another section of this report discusses unresolved problems surrounding recruiter acceptance of modern employee selection technologies.

Further, results for the most influential authors in the field, co-cited documents, etc., also help researchers for a better understanding of AI in HRM, as presented in Table 4. Papers of various authors discussed the concepts related to AI and HRM integration. Strohmeier and Piazza (2015) research offered an exploration of the general potential of AI techniques (neural networks, genetic algorithms, text mining, interactive voice response etc.) in HRM (turnover prediction, staff rostering, HR sentiment analysis etc.).

Jantan et al. (2008) have discussed in their paper that HR decisions are subject to limitations. An Intelligent Decision Support System (IDSS) is developed to assist decision-makers in high-level decision-making phases by integrating human knowledge with modelling tools. The paper by Liu et al. (2019a, b, c) attempts to put forward ideas on a data-driven solution for the promotion issue in HRM. It focuses on the influence of the position of an organization. They further adopt the data-driven methods of data analytics to explore employee growth based on interpersonal environment factors, providing insights into employee growth by carrying out quantitative analysis, and designing exact prediction models. Liu et al. (2018) studied technologies such as data mining and machine learning, to explore employee turnover more thoroughly and efficiently. Wang and Wang (2017) explored a knowledge-based HR system that includes expert knowledge system, AI technology, neural network, knowledge management, and pattern recognition technology and theory.

Wang (2008) analyzed employee turnover risk factors that would threaten enterprise production and operation activities, and then proposed a decision support system of employee turnover risk management, realized by message processing mechanism, software combination technology and system integration, and set up the corresponding management strategies to manage the risk effectively. Prentice et al. (2020) have integrated the two concepts of emotional factors and AI, and their influence on employee retention and performance, with a focus on service employees in the hotel industry.

Their research also discussed that employee performance is operationalized into internal and external dimensions that capture employees' task efficiency over internal and external service encounters with co-workers and customers. Further, El-Rayes et al. (2020) paper centered around employee attrition using tree-based models. Yu et al. (2019) talked about multi-agent reinforcement learning and mobile sensing robots. Vinichenko et al. (2019) discussed AI in the talent management system.

Vinichenko et al. (2020) analyzed the positive and negative impact of AI on the behavior of people in the labor market, by assessing the effectiveness of human potential use, human learning and competitiveness, increase (decrease) in unemployment, social inequality, impact on the human psyche and its safety. Thus, it can be concluded from the earlier discussion that most studies of influential authors in this area help to develop a conceptual framework for future research.

7 Analysis of author keyword

This part helped in studying the subject-related flow of knowledge through evaluation of an author's keyword. Strozzi et al. (2017) explained that it encompasses a measure of outstanding document content or the paper's relative content. Consequently, researchers have also executed this analysis to view the study movement in

AI and diverse HRM functions in the organization. Researchers first extricated these keywords from a set of 344 related papers; then, the same network was built with the help of VOSviewer. To produce systematic results, researchers set a limit of five least co-occurrence of keywords. Finally, researchers obtained 963 keywords and extracted the top 30 keywords. It was found that AI is the maximum co-occurring keyword, with a frequency of 55.

The network in Fig. 6 shows AI as the most significant node. The keywords connected to a homogeneous group are displayed in a similar colour. It can be seen that the keyword AI is portrayed in several ways, such as AI, big data and HR, and these keywords exist in nearly all the sets. The words HRM, fuzzy logic, people analytics, HR analytics, and management co-exist in the same cluster. It suggests that research on AI and HRM has been done on multiple aspects (Fig. 6). This analysis proved that machine learning, big data, talent management, employee attrition and decision support system are the most studied topics in the context of AI and HRM (Fig. 7).

It can also be concluded from Fig. 1, which shows the topic trend over the period, that the most highly discussed topics are AI and HRM. Further, Fig. 8 also shows the trend of most-studied topics for the last four years.

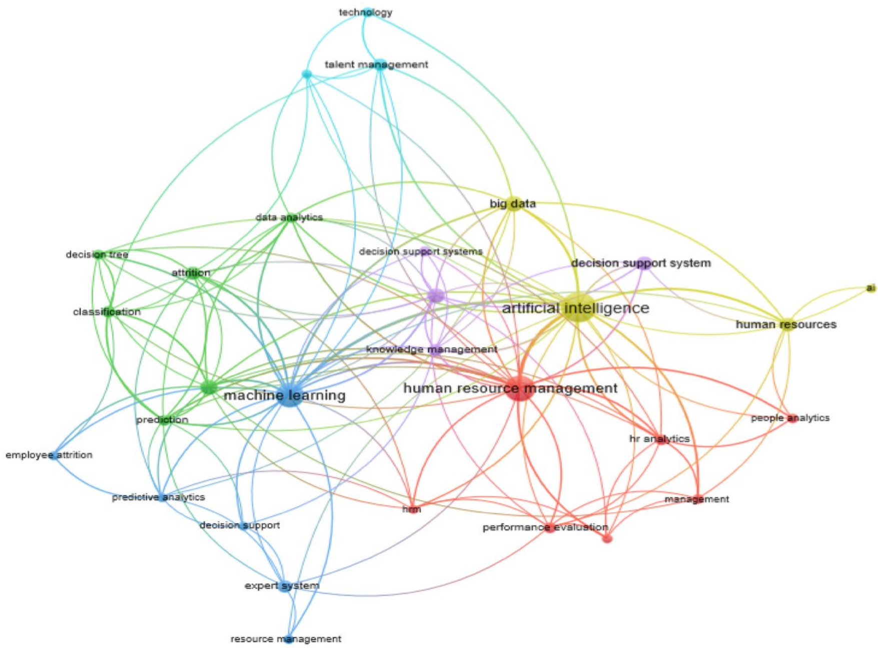

Fig. 6 Author keyword network (*Source*: Authors)

Fig. 7 Evolution of top keywords in "AI and HRM" publications (*Source*: Authors)

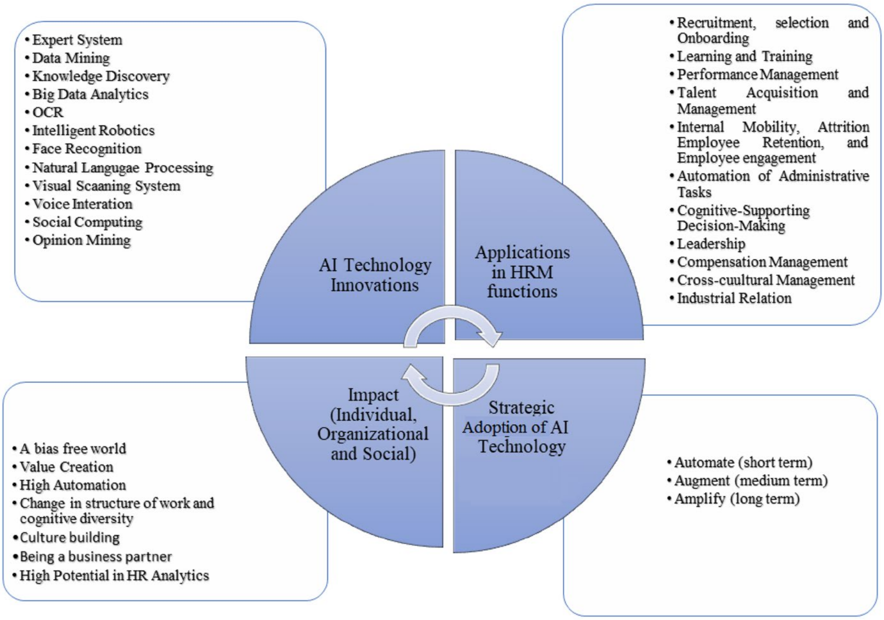

Fig. 8 Framework for AI and HRM integration (*Source*: Authors)

8 Gaps identified in the current literature study

Through this comprehensive evaluation of literature, researchers have established that there has been a constant improvement in the structure of articles. There are substantial gaps in the study hampering the progress of the theme. The two clusters mainly discussed the context of HR functions and AI. Consequently, researchers recommend three courses of action for a study on AI and HRM in organizations:

1. *Less research work for more significant HRM functions in the context of AI and HRM such as cross-cultural management, industrial relation and compensation management* All research discussed in the current paper throws light on some of

the major functions of HRM. AI technologies impact some functions: recruitment, selection, onboarding, training and learning, performance analysis, talent acquisition, management, retention, etc. Researchers have discussed less some other significant HRM functions such as cross-cultural management, industrial relations and compensation management. Researchers also highlight the importance of the topic of cross-cultural management. Wu et al. (2012) proposed an AI-based model (CIDSS) that enables companies and individuals to make intelligent decisions in culturally diversified organizational activities, and resolves the intercultural problems encountered in a variety of authentic cross-cultural circumstances. Further, it has also been viewed that in an extensive search for articles on AI and HRM, fewer results are shown for the functions compensation management and industrial relation.

2. *Lack of cross-sector and country collaboration of Artificial Intelligence* Cross-sectoral collective perspective is the norm in AI centres of eminence around the globe. Regardless of their demand, cross-sector collaborations invite serious management challenges that hamper their accomplishment (Mikhaylov et al. 2018). Blanchard and Frasson (2005) validated the use of dimensions of individualism or collectivism, proposed by Hofstede, in ethnically cognizant systems of e-learning in the future. It recommends an architecture for culturally aware systems for e-learning where academics represent the concept of culturally intelligent agents. The study presented elements that help management and cross-cultural psychology fields strengthen e-learning systems using cultural considerations. So, various related articles that have been published from 2005 on the theme AI and HRM, researchers can conclude that there is a lack of the earlier-discussed elements. Further, it has been found that only country-specific cases related to AI and HRM are available and not comparative studies of countries. The studies of various researchers like Petruzzellis et al. (2006a, b), Zhang et al. (2012), Iwamoto (2019), Abdeldayem and Aldulaimi (2020), Prem (2019), Liu et al. (2019a, b, c), Moyo et al. (2018), Norikumo (2019) etc., have discussed country-specific cases of AI and HRM.
3. *Less availability of cross-sector collaboration* studies has also been implied in researchers' studies that discussed only a particular sector. Various authors such as Dabirian (2019), Nawaz (2019), Nijjer et al. (2019), Hosseininezhad et al. (2011), Khera and Divya (2018) and Colomo-Palacios et al. (2014) have specifically discussed various HRM functions and AI integration in the IT and software sectors. Nawaz's (2019) study aimed at knowing AI substituting human involvement in the recruitment process in selected software companies in India. Dabirian (2019) discussed employer branding in the IT industry in a special context to the employer. Khera and Divya (2018) study depicted predictive modeling of employee turnover in the Indian IT industry using machine learning techniques. Further, Tursunbayeva's (2019) and Reddy et al. (2019) studies concentrated on I-competere and HR technology disruptions for implication in HRM in healthcare organizations. The other major sectors covered by writers in some studies are as follows: Sánchez et al. (2016), Brockmann et al. (2019), Fajar et al. (2018), and Mitrofanova et al. (2020) covered the education sector, Zhang et al. (2012) stud-

ied the banking sector, Hughes and Rog (2008) the hospitality sector, Norikumo (2019) the insurance sector etc.

The earlier discussed gaps played a very significant role in several organizations. Researchers believe that filling such gaps would help top leaders, strategic planners and policymakers in the future challenges of the HR industry. The academia would be able to understand and train next-generation HR professionals on the mentioned gaps.

9 Future research directions and implications

The detailed analysis identifies some vital directions for future work with the proposed AIHRMI framework. The researchers first mapped the trend of publication by the year, disciplinary distribution and analysis of keywords and content, to show emerging topics, and bibliometric analysis. Finally, the current paper proposes an AIHRMI framework to overcome all the limitations of previous studies and the recently discussed bibliometric section findings. All the cluster data derived from the CA, such as HR analytics, HRIS, big data and HRM functions integration with AI, have been included in the proposed AIHRMI framework.

Additionally, gaps identified from the CA indicate that scope for research work exists for more significant HRM functions in the context of AI and HRM, namely, cross-cultural management, industrial relations, compensation management, and lack of cross-sector and country collaboration of AI. Cross-cultural and sector collaboration also leads management to face more challenges that hamper the organization's performance. Bridging all the identified gaps can help HR professionals to perform effectively. So, gaps discussion has been proposed for future research with four main parts, as shown in Fig. 8 for the AIHRMI framework. Nowadays, researchers are also interested in high-performance work systems (HPWS). Researchers may further seek an integrated version of HPWS along with AIHRMI.

Thus, the study proposes a comprehensive framework based on insights yielded by the bibliometrics and content analyses of prior AI and HRM literature. In addition to bibliometric and CA for designing the framework, extant research extracted from the literature on the framework for AI and HRM function such as Duchessi et al. (1993), Liang and Liu (2018), and Jia et al. (2018), have also remained its basis. Finally, all the earlier-discussed contexts (bibliometric, SLR, CA, previous AI, and HRM model-based studies and gaps identified in the current study) have been used to develop the framework.

Figure 8 presents an overall framework that divides the study themes into four dimensions: AI technological innovations, their implementation in HRM functions, impact and strategic adoption of AI technology. In each dimension, numerous probable topics require further exploration. The first dimension, for instance, embraces various technologies invented with AI. These innovations include data mining, expert systems, big data analytics, NLP etc. Collection, storage and analysis of data under such innovative technologies help integrate various HRM functions.

Applications of AI in various HRM functions can be integrated differently. In recruitment selection and onboarding, AI technologies, expert systems, data mining, big data analytics, and NLP are pivotal. For training and development, performance analysis, talent acquisition, management and retention, visual scanning system, voice recognition, face recognition, and knowledge recovery are making domain functions very significant.

As discussed in the previous section on gaps identified in the current literature study, it would be interesting to bridge these gaps. In the first gap of the study, it has been found that cross-cultural management, industrial relations and compensation management as HR functions are found to be less discussed arenas. But as AI works as an intelligent virtual assistant (IVA) in cross-cultural management, AI can facilitate communication that can be as productive and inclusive as possible. For its effective implementation, companies' technology should be equipped to understand individuals from diverse cultural backgrounds, without bias. Otherwise, it will not be possible to get the desired results, and people will run the risk of being alienated from the "connected," AI-powered world.

Further, a continuing concern of the labour market is compensation, as workers seek to be paid for their value. With HR continuing to evolve, it is important also to change how compensation is determined. Organizations need a more comprehensive range of data to create a strategy that works for their people and matches differences in expectations, roles and skill sets.AI helps to provide market insights and increase recruiting efficacy.

Another gap identified in the current study is to achieve the highest potential of the AI cross-sectoral collaboration as suggested in the AI sector deal. Success factors of similar enterprises around the world must be considered. In a nutshell, facilitative leadership is imperative for collaboration success. In addition, alignment of goals and objectives between all the involved parties has also been identified as a key factor for collaboration success. Hence, researchers, organizations, and policymakers must take concerns exclusive to AI implementation areas into various HRM functions while researching for academic purposes or implementing it in an organization.

Moreover, the benefits of AI in HRM functions do not come instantly. It can prove its effectiveness with the adoption of a proper strategic journey. In place of taking short-term benefits, organizations can proceed with automation of monotonous and more time-taking tasks. Further, to get medium-term benefits, the expansion of human proficiencies can proceed. Third, to prove its strategic effectiveness, the amplification of human functions can be taken up. The strategic adoption of AI in HRM functions also has three levels of impact i.e., individual, organizational and social (Keding 2021). These impacts include a bias-free world, automation and value creation etc. Further, studies on various issues and challenges (cost–benefit assessment, security and privacy issues, etc.) faced during the adoption of AI technologies should also be taken into consideration.

Management of organizations should also include the factors which affect the adoption of AI technology. Thus, the proposed AIHRMI framework will help to take full advantage of this collaboration (AI and HRM functions); companies must understand how humans can most effectively augment machines, how machines can enhance what humans do best, and how to redesign business processes to support the partnership. Current research enables companies achieve and put the power of collaborative intelligence to work.

10 Conclusions

This study aims to clarify how AI has been integrated into diverse HR functions and its influence in the direction of organizations, workforces, and HR. The model will provide ideas and directions for the expansion of AI in HRM for various organizations. This study can be concluded in the following way:

This paper consists of two parts. The first part reports results from SLR, bibliometric and CA, and classifies the literature on AI and HRM functions integration into five different clusters. The second part discusses the main findings of the AIHRMI framework. Theoretical and practical contributions of the study are as follows.

10.1 Theoretical implications

Two main theoretical implications are: first, the evolutionary journey and IS of literature by analysis of suggesting five clusters are documented. These clusters facilitated in recognizing that the study on AI and HRM in various organizations can be divided into five foremost streams. Cluster I was developed in 1996 and it discussed various areas of HR analytics such as its effectiveness, potentialities, transformative role and related benefits. Studies in this cluster highlighted content concerning the effectiveness of HR analytics which aim to provide insights into each process by gathering data and then using it to take relevant steps to improve processes, i.e., such as talent acquisition, training and induction, performance review, compensation, rewards and benefits, and employee retention. This cluster of experts has summarized that HR analytics must be proficient in ensuring the future of HR as a strategic management tool while improving organizational efficiency.

Cluster II has developed consistently since 1985 with the central theme of the HRIS. As per this cluster, a balance between global integration and local responsiveness should be made by maintaining operational issues and strategic considerations to strike for the overall effectiveness of an organization in the context of HRIS. Further, the researchers discussed that the HRIS model is a basis for planning, designing, implementing successful systems, and is a critical requirement for any organization.

Cluster III is the most significant as the documents under it discussed various HRM functions like job rotation system, training terms, calculation and determination of salary parameters, HR planning, suitable staff selection, employee turnover etc., with its inclusion in varied AI techniques i.e., expert system decision-making, Data Mining System, logistic regression, neural network, machine learning, etc. Thus, it has been concluded from this cluster discussion that various AI technologies have a significant impact on HRM functions.

The second part provides directions for research in the future. Academicians involved with AI and HRM studies may ascertain the framework shown in Fig. 8 of this paper to position their research. The significant content variables analysis has remained the foundation for the development of AI in the field of HRM. HRIS contributes to the growth of human–computer interaction functions of AI, creating opportunities for managers to advance management proficiency employing AI. However, connected with AIHRMI, the information systems are further responsible for data input and preservation; the intelligence decision assistance role is still restricted.AI will further improve the business analytics capabilities of the machine to provide more reference and efficiency for decision-making. Big data, the next variable of the cluster under CA, provides fuel for AI development.

Interestingly, AI has played a tremendous role within HR to promote smart people analytics in creative ways to recruit top talent. Consequently, it has been found that research on AI and HRM has been increasing gradually as researchers are taking extreme interest in various areas of the current theme. This framework will further guide research and practice in the domain of AI and HRM.

10.2 Practical implications

The three main practical implications are as follows. First, IS and the comprehensive framework of the AI and HRM functions literature developed in the present study offer valuable insights into practitioners for better understanding the influence of AI technologies in increasing the effectiveness of various HRM functions. Furthermore, it helps them to understand the importance of AI technologies in conjunction with HRM practices for achieving sustainable competitive advantage.

Second, a concrete understanding of various aspects of AI and HRM has been presented, which can enable practitioners to develop a strategic vision and formulate more effective strategies for deployment of the impact of AI/machine learning on the labor market as it always remains an under-investigated subject in context to emerging economies (Brynjolfsson and Mitchell 2017). Furthermore, it will provide an understanding of the underlying mechanisms in the context of AI and HRM for various organizations.

Third, policymakers may obtain insights from the current study's findings for policy formulation. The comprehensive framework (AIHRMI) implementation will help maintain competitive advantage. Organizations can plan for AI transformation by gradually building the internal data analytics system and improving enterprise information management. To bring in the effectiveness of this framework and increase the likelihood of success, managers must adopt a long-term vision for its implementation. Moreover, they should peg the status quo, increase resources, lead with transparency, and work out bugs before scaling to the rest of the organization. It will also help as a leadership initiative for the fourth industrial revolution.

In conjunction with apex collaborators in this area, researchers have established the movement and accomplishment of study themes on AI and HRM in the current environment by evaluating the five clusters attained from CoC NA (network analysis). From the implementation point of view, this analysis can assist as a fundamental base for considering the study area of AI integration with HR, its recent footpace, and the direction where research is mounting. Moreover, it features a gap in the existing frame of knowledge and recommends three applicable paths for further research on the topic.

10.3 Limitations

This study is based on the literature review of AI and HRM, with specified and all-inclusive search terms on the theme, and attained a figure of 344 papers after the refinement process from both the databases in the past 21 years (2000–2020). If the researcher had used other keywords, then it would have yielded different results. Gathering available knowledge is a critical part of the SLR.

Although the study comprises 344 articles extracted from the Scopus database, it has certain limitations too. In future, a more extensive study can be conducted, considering multiple databases along with WoS. Further, researchers used two software packages in the current study, Biblioshiny and VOSviewer, instead of multiple software. Researchers have classified the literature into five research clusters with the help of Biblioshiny software. Other methods and software *(*VOSviewer*)* may result in other classifications.

Another important limitation is that this study is a weak comprehension of different theories used in the major research domain. However, apt and required theories are amalgamated in this paper. Further researches of this domain could explore a few new dimensions.

Despite the limitations mentioned earlier, this paper is the first attempt in the direction to provide a comprehensive review of the research undertaken on the AI and HRM functions. It presents a complete thematic flow of knowledge and identifies directions for upcoming researchers to study new topics in the future. This will help the extension and advancement of research on this topic.

Appendix

The most productive and significant authors

Sr. No	Authors	Affiliation	Country	TP
1	Strohmeier S	Chair of Management Information Systems, Saarland University, Saarbrücken, Germany	Germany	6
2	LIU J	National University of Defense Technology	China	5
3	Wang T	National University of Defense Technology	China	5
4	Wang X	School of Computer Science and Technology, Dalian University of Technology, Dalian, China	China	4
5	Hulanova OL	Department of State and Municipal Management, Surgut State University	Russian Federation	3
6	Fang M	College of Systems Engineering, National University of Defense Technology, Changsha, 410073, China	China	3

The most productive and significant authors				
Sr. No	Authors	Affiliation	Country	TP
7	Hamdan AR	Faculty of Information Science and Technology, UKM, Bangi, Selangor	Malaysia	3
8	HE R	National University of Defense Technology, Changsha	China	3
9	Jantan H	Faculty of Computer Science and Mathematics, Universiti Teknologi MARA (Uitm) Terengganu, Dungun, Terengganu	Malaysia	3
10	Othman ZA	Faculty of Information Science and Technology, UKM, Bangi, Selangor	Malaysia	3

Main co-author coupling		
Sr. No	Authors	Count of joint publications
1	Liu J., Wang T	4
2	Liu J., He R., Wang T	3
3	Jantan H., Hamdan A.R., Othman Z.A	3
4	Vinichenko M.V., Hulanova O.L., Rybakova M.V	3
5	Liu J., Li J., Wang T., He R	2
6	Petruzzellis S., Licchelli O., Palmisano I., Bavaro V., Palmisano C	2
7	Vinichenko M.V., Hulanova O.L., Rybakova M.V., Makushkin S.A	2
8	Vinichenko M.V., Hulanova O.L., Rybakova M.V., Malyshev M.A	2

Total citation of the articles of top journals			
Sr. No	Sources	Articles	TC
1	Advances in Intelligent Systems and Computing	21	11
2	Communications in Computer and Information Science	5	9
3	Expert Systems with Applications	5	132
4	Frontiers in Artificial Intelligence and Applications	5	31
5	International Journal of Recent Technology and Engineering	5	3
6	International Journal of Scientific and Technology Research	4	1
7	Computers in Human Behavior	4	30
8	International Journal of Advanced Science and Technology	4	0
9	Procedia Computer Science	3	7
10	Boletin Tecnico/Technical Bulletin	3	0

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Declarations

Ethics approval Not applicable.

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References

Abdeldayem MM, Aldulaimi SH (2020) Trends and opportunities of artificial intelligence in human resource management: aspirations for public sector in Bahrain. Int J Sci Technol Res 9(1):3867–3871

Acedo FJ, Barroso C, Casanueva C, Galán JL (2006) Co-authorship in management and organizational studies: an empirical and network analysis. J Manag Stud 43(5):957–983. https://doi.org/10.1111/j.1467-6486.2006.00625.x

Anderson N (2003) Applicant and recruiter reactions to new technology in selection: a critical review and agenda for future research. Int J Sel Assess 11(2/3):121–136. https://doi.org/10.1111/1468-2389.00235

Angrave D, Charlwood A, Kirkpatrick I, Lawrence M, Stuart M (2016) HR and analytics: why HR is set to fail the big data challenge. Hum Res Manag J 26(1):1–11. https://doi.org/10.1111/1748-8583.12090

Aral S, Brynjolfsson E, Wu L (2012) Three-way complementarities: performance pay, human resource analytics, and information technology. Manage Sci 58(5):913–931

Bassi L (2011) Raging debates in HR analytics. People Strategy 34(2):14

Baxter M (2018) Information-age. https://www.information-age.com/business-analytics-intelligence-123477004/. Accessed 26 June 2020

Becker B, Gerhart B (1996) The impact of human resource management on organizational performance: Progress and prospects. Acad Manag J 39(4):779–801

Berhil S, Benlahmar H, Labani N (2020) A review paper on artificial intelligence at the service of human resources management. Indones J Electr Eng Comput Sci 18(1):32–40. https://doi.org/10.11591/ijeecs.v18.i1.pp32-40

Beg MMH (2019) Re: employee-retention/talent-retention-using-artificial-intelligence. https://sightsinplus.com/insight/employee-retention/talent-retention-using-artificial-intelligence/

Bersin J (2018) Talent trends technology disruptions for 2018. https://www.isaconnection.org/assets/documents/2018BersinHRTechDisruptionsReport.pdf

Blanchard EG, Frasson C (2005) Making intelligent tutoring systems culturally aware: The use of Hofstede's cultural dimensions. In: IC-AI, pp 644–649

Block JH, Fisch C (2020) Eight tips and questions for your bibliographic study in business and management research. Manag Rev Q 70(3):307–312. https://doi.org/10.1007/s11301-020-00188-4

Blondel VD, Guillaume JL, Lambiotte R, Lefebvre E (2008) Fast unfolding of communities in large networks. J Stat Mech Theory Exp 10:P10008. https://doi.org/10.1088/1742-5468/2008/10/P10008

Bondarouk T, Brewster C (2016) Conceptualising the future of HRM and technology research. Int J Hum Resour Manag 27(21):2652–2671. https://doi.org/10.1080/09585192.2016.1232296

Brockmann P, Schuhbauer H, Hinze A (2019) Diversity as an Advantage: An Analysis of Career Competencies for IT Students. In: 16th international conference cognition and exploratory learning in digital age, CELDA, pp 209–216. https://doi.org/10.33965/celda2019_201911L026

Brynjolfsson E, Mitchell T (2017) What can machine learning do? Workforce implications. Science 358:1530–1534. https://doi.org/10.1126/science.aap8062

Brin S, Page L (1998) The anatomy of a large-scale hypertextual web search engine. Comput Netw ISDN Syst 30:107–117. https://doi.org/10.1016/S0169-7552(98)00110-X

Castriotta M, Loi M, Marku E, Naitana L (2019) What's in a name? Exploring the conceptual structure of emerging organizations. Scientometrics 118(2):407–437. https://doi.org/10.1007/s11192-018-2977-2

Prentice C, Lopes SD, Wang X (2020) Emotional intelligence or artificial intelligence—an employee perspective. J Hosp Mark Manag 29(4):377–403. https://doi.org/10.1080/19368623.2019.1647124
Chamorro-Premuzic T, Winsborough D, Sherman RA, Hogan R (2016) New talent signals: Shiny new objects or a brave new world? Ind Organ Psychol 9(3):621–640. https://doi.org/10.1017/iop.2016.6
Chen H, Chiang RH, Storey VC (2012) Business intelligence and analytics: from big data to big impact. MIS Q. https://doi.org/10.2307/41703503
Chien CF, Chen LF (2008) Data mining to improve personnel selection and enhance human capital: a case study in high-technology industry. Expert Syst Appl 34(1):280–290. https://doi.org/10.1016/j.eswa.2006.09.003
Cisneros L, Ibanescu M, Keen C, Lobato-Calleros O, Niebla-Zatarain J (2018) Bibliometric study of family business succession between 1939 and 2017: mapping and analyzing authors' networks. Scientometrics 117(2):919–951. https://doi.org/10.1007/s11192-018-2889-1
Colomo-Palacios R, González-Carrasco I, López-Cuadrado JL, Trigo A, Varajao JE (2014) I-Competere: using applied intelligence in search of competency gaps in software project managers. Inf Syst Front 16(4):607–625. https://doi.org/10.1007/s10796-012-9369-6
Dabirian A (2019) Employer branding in the IT industry: AN employer view. In: 2019 IEEE 43rd annual computer software and applications conference (COMPSAC), vol 1, pp 548–548. IEEE. https://doi.org/10.1109/COMPSAC.2019.00084
De Kok J, Uhlaner LM (2001) Organisation context and human resource management in the small firm. Small Bus Econ 17(4):273–291. https://doi.org/10.1023/A:1012238224409
DeSanctis G (1986) Human resource information systems: a current assessment. MIS Q 10:15–27. https://doi.org/10.2307/248875
Ding Y, Cronin B (2011) Popular and/or prestigious? Measures of scholarly esteem. Inf Process Manag 47(1):80–96. https://doi.org/10.1016/j.ipm.2010.01.002
Ding Y, Yan E, Frazho A, Caverlee J (2009) PageRank for ranking authors in co-citation networks. J Am Soc Inf Sci 60:2229–2243. https://doi.org/10.1002/asi.21171
Dubey R, Gunasekaran A, Childe SJ (2019) Big data analytics capability in supply chain agility. Manag Decis 57(8):2092–2112. https://doi.org/10.1108/MD-01-2018-01192092-2112
Duchessi P, O'Keefe R, O'Leary D (1993) A research perspective: artificial intelligence, management and organizations. Int J Intell Syst Accounting Financ Manag 2(3):151–159. https://doi.org/10.1002/j.1099-1174.1993.tb00039.x
Dwivedi YK, Hughes L, Ismagilova E, Aarts G, Coombs C, Crick T, Galanos V (2019) Artificial intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. Int J Inf Manage. https://doi.org/10.1016/j.ijinfomgt.2019.08.002
El-Rayes N, Fang M, Smith M, Taylor SM (2020) Predicting employee attrition using tree-based models. Int J Organ Anal 28(6):1273–1291. https://doi.org/10.1108/IJOA-10-2019-1903
Erixon F (2018) Recipe. Retrieved from the economic benefits of globalization for business and consumers. https://ecipe.org/publications/the-economic-benefits-of-globalization-
Fan CY, Fan PS, Chan TY, Chang SH (2012) Using hybrid data mining and machine learning clustering analysis to predict the turnover rate for technology professionals. Expert Syst Appl 39(10):8844–8851. https://doi.org/10.1016/j.eswa.2012.02.005
Fajar AN, Nurcahyo A, Sriratnasari SR (2018) SOA System architecture for interconnected modern higher education in Indonesia. Procedia Computer Science 135:354–360. https://doi.org/10.1016/j.procs.2018.08.184
Fisch C, Block J (2018) Six tips for your (systematic) literature review in business and management research. Manag Rev Q 68(2):103–106. https://doi.org/10.1007/s11301-018-0142-x
Frisk JE, Bannister F (2017) Improving the use of analytics and big data by changing the decision-making culture. Manag Decis 55(10):2074–2088. https://doi.org/10.1108/MD-07-2016-0460
Galanaki E, Lazazzara A, Parry E (2019) A cross-national analysis of E-HRM configurations: integrating the information technology and HRM perspectives. In: Lazazzara A, Nacamulli R, Rossignoli C, Za S (eds) Organizing for digital innovation. Lecture notes in information systems and organisation, vol 27. Springer, Cham, pp 261–276. https://doi.org/10.1007/978-3-319-90500-6_20
Glänzel W, Schubert A (2004) Analyzing scientific networks through co-authorship. In: Glänzel W, Schmoch U (eds) Handbook of quantitative science and technology research. Springer, Dordrecht, pp 257–276. https://doi.org/10.1007/1-4020-2755-9_12
Gmür M (2003) Co-citation analysis and the search for invisible colleges: a methodological evaluation. Scientometrics 57(1):27–57. https://doi.org/10.1023/A:1023619503005

Góes ASDO, De Oliveira RCL (2020) A Process for human resource performance evaluation using computational intelligence: an approach using a combination of rule-based classifiers and supervised learning algorithms. IEEE Access 8:39403–39419. https://doi.org/10.1109/ACCESS.2020.2975485

Kluemper DH, Rosen PA (2009) Future employment selection methods: evaluating social networking web sites. J Manag Psychol 24(6):567–580. https://doi.org/10.1108/02683940910974134

Haines VY, Petit A (1997) Conditions for successful human resource information systems. Hum Resour Manag 36(2):261–275. https://doi.org/10.1002/(SICI)1099-050X(199722)36:2%3c261::AID-HRM7%3e3.0.CO;2-V

Hannon J, Jelf G, Brandes D (1996) Human resource information systems: operational issues and strategic considerations in a global environment. Int J Hum Resour Manag 7(1):245–269. https://doi.org/10.1080/09585199600000127

HireVue (2017) HireVue: case study. https://cdn2.hubspot.net/hubfs/464889/Hilton%20Aug%202017/2017_12_SuccessStory_Hilton_CustomerMarketing3.pdf?__hstc=&__hssc=&hsCtaTracking=b76cefe9-cece-4631-bef5-53084aa900e5%7Ca26c5bca-5fbe-46e3-b0e4-c1f79894f72c

Holland JH (1992) Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence, 1st edn. MIT Press, pp 1–207

Hosseininezhad F, Nadali A, Balalpour M (2011) A Fuzzy Expert System for performance evaluation of HRM with 360 degree feedback approach (Case study: An Iranian IT company). In: 2011 6th international conference on computer sciences and convergence information technology (ICCIT), pp 487–491. IEEE.

Huai C, Chai L (2016) A bibliometric analysis on the performance and underlying dynamic patterns of water security research. Scientometrics 108(3):1531–1551. https://doi.org/10.1007/s11192-016-2019-x

Hughes JC, Rog E (2008) Talent management: a strategy for improving employee recruitment, retention and engagement within hospitality organizations. Int J Contemp Hosp Manag 20(7):743–757. https://doi.org/10.1108/09596110810899086

Huselid MA (1995) The impact of human resource management practices on turnover, productivity, and corporate financial performance. Acad Manag J 38(3):635–672

Iwamoto T (2019) Development of the HR tech market in Japan. In: 2019 Portland international conference on management of engineering and technology (PICMET). IEEE, pp 1–4. https://doi.org/10.23919/PICMET.2019.8893759

Jantan H, Hamdan AR, Othman ZA (2008) Potential intelligent techniques in human resource decision support system (HR DSS). In: 2008 international symposium on information technology. IEEE. vol 3, pp 1–9.https://doi.org/10.1109/ITSIM.2008.4632047

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, pp 106–114. https://aisel.aisnet.org/iceb2018/91

Kamaruddin N, Rahman AWA, Lawi RAM (2019) Jobseeker-industry matching system using automated keyword selection and visualization approach. Indones J Electr Eng Comput Sci 13(3):1124–1129. https://doi.org/10.11591/ijeecs.v13.i3.pp1124-1129

Katz JS, Martin BR (1997) What is research collaboration? Res Policy 26:1–18. https://doi.org/10.1016/S0048-7333(96)00917-1

Keding C (2021) Understanding the interplay of artificial intelligence and strategic management: four decades of research in review. Manag Rev Q 71:91–134. https://doi.org/10.1007/s11301-020-00181-x

Khera SN, Divya (2018) Predictive modelling of employee turnover in Indian IT industry using machine learning techniques. Vision 23(1):12–21. https://doi.org/10.1177/0972262918821221

Kluemper DH, Rosen PA, Mossholder KW (2012) Social networking websites, personality ratings, and the organizational context: more than meets the eye? J Appl Soc Psychol 42(5):1143–1172. https://doi.org/10.1111/j.1559-1816.2011.00881.x

LaValle S, Lesser E, Shockley R, Hopkins MS, Kruschwitz N (2011) Big data, analytics and the path from insights to value. MIT Sloan Manag Rev 52(2):21–32

Lawler JJ, Elliot R (1996) Artificial intelligence in HRM: an experimental study of an expert system. J Manage 22(1):85–111. https://doi.org/10.1016/S0149-2063(96)90013-6

Legris P, Ingham J, Collerette P (2003) Why do people use information technology? A critical review of the technology acceptance model. Inf Manag 40(3):191–204. https://doi.org/10.1016/S0378-7206(01)00143-4

Leydesdorff L (2015) Bibliometrics/citation networks. In: Barnett GA (ed) Encyclopaedia of social networks. Sage Publications Inc, Thousand Oaks

Liang TP, Liu YH (2018) Research landscape of business intelligence and big data analytics: a bibliometrics study. Expert Syst Appl 111:2–10. https://doi.org/10.1016/j.eswa.2018.05.018

Lievens F, Sackett PR (2006) Video-based versus written situational judgment tests: a comparison in terms of predictive validity. J Appl Psychol 91(5):1181. https://doi.org/10.1037/0021-9010.91.5.1181

Liu C, Li Z, Zhou D, Shi Y (2019) Organizational innovation of Sci-Tech societies in the era of intelligence: a case study in China. In: 2019 Portland international conference on management of engineering and technology (PICMET). IEEE, pp 1–7. https://doi.org/10.23919/PICMET.2019.8893783

Liu J, Wang T, Li J, Huang J, Yao F, He R (2019) A data-driven analysis of employee promotion: the role of the position of organization. In: 2019 IEEE international conference on systems, man and cybernetics (SMC). IEEE, pp 4056–4062. https://doi.org/10.1109/SMC.2019.8914449

Liu J, Li J, Wang T, He R (2019) Will your classmates and colleagues affect your development in the workplace: predicting employees' growth based on interpersonal environment. In: 2019 IEEE fifth international conference on big data computing service and applications (Big Data Service). IEEE, pp 71–78. ISBN Information: INSPEC Accession Number: 19013694. https://doi.org/10.1109/BigDataService.2019.00016

Liu J, Long Y, Fang M, He R, Wang T, Chen G (2018) Analyzing employee turnover based on job skills. In: Proceedings of the international conference on data processing and applications, pp 16–21. https://doi.org/10.1145/3224207.3224209

Mahmoud AA, Shawabkeh TA, Salameh WA, Al Amro I (2019) Performance predicting in hiring process and performance appraisals using machine learning. In: 2019 10th international conference on information and communication systems (ICICS). IEEE, pp110–115. https://doi.org/10.1109/IACS.2019.8809154

Mallick Basu Chiradeep (2019) Re: how-ai-identifies-flight-risk-and-helps-retain-highvalue-employees. https://www.hrtechnologist.com/articles/digital-transformation/how-ai-identifies-flight-risk-and-helps-retain-highvalue-employees/

Marler JH, Boudreau JW (2017) An evidence-based review of HR Analytics. Int J Hum Resour Manag 28(1):3–26. https://doi.org/10.1080/09585192.2016.1244699

McAfee A, Brynjolfsson E, Davenport TH, Patil DJ, Barton D (2012) Big data: the management revolution. Harv Bus Rev 90(10):60–68

McCarthy J, Minsky ML, Rochester N, Shannon CE (1955) A proposal for the Dartmouth summer research project on artificial intelligence, august 31. AI Mag 27(4):12–12

McDonald K, Fisher S, Connelly CE (2017) e-HRM systems in support of "smart" workforce management: An exploratory case study of system success. Electronic HRM in the smart era, 87–108. https://doi.org/10.1108/978-1-78714-315-920161004; https://doi.org/10.1609/aimag.v27i4.1904

Mehrabad MS, Brojeny MF (2007) The development of an expert system for effective selection and appointment of job applicants in human resource management. Comput Ind Eng 53(2):306–312. https://doi.org/10.1016/j.cie.2007.06.023

Melin G, Persson O (1996) Studying research collaboration using co-authorships. Scientometrics 36:363–377

Mikhaylov SJ, Esteve M, Campion A (2018) Artificial intelligence for the public sector: opportunities and challenges of cross-sector collaboration. Philos Trans R Soc Math Phys Eng Sci 376(2128):20170357. https://doi.org/10.1098/rsta.2017.0357

Mitchell RS, Michalski JG, Carbonell TM (2013) An artificial intelligence approach. Springer, Berlin

Mitrofanova E, Mitrofanova A, Tarasenko V (2020) Immature digital expertise of the educational institution's managerial staff as HR risk to education development. In: 13th international scientific and practical conference-artificial intelligence anthropogenic nature vs. social origin. Springer, Cham, pp 756–765. https://doi.org/10.1007/978-3-030-39319-9_84

Montuschi P, Gatteschi V, Lamberti F, Sanna A, Demartini C (2013) Job recruitment and job-seeking processes: how technology can help. IT Professional 16(5):41–49. https://doi.org/10.1109/MITP.2013.62

Moyo S, Doan TN, Yun JA, Tshuma N (2018) Application of machine learning models in predicting length of stay among healthcare workers in underserved communities in South Africa. Hum Resour Health 16(1):68. https://doi.org/10.1186/s12960-018-0329-1

Nawaz N, Gomes AM (2019) Artificial intelligence chatbots are new recruiters. Int J Adv Comput Sci Appl. https://doi.org/10.14569/IJACSA.2019.0100901

Nawaz N (2019) Artificial intelligence interchange human intervention in the recruitment process in Indian software industry. Int J Adv Trends Comput Sci Eng. https://doi.org/10.2139/ssrn.3521912

Newman MEJ (2001) The structure of scientific collaboration networks. Proc Natl Acad Sci 98:404–409. https://doi.org/10.1073/pnas.021544898

Newman MEJ (2004) Coauthorship networks and patterns of scientific collaboration. Proc Natl Acad Sci 101:5200–5205. https://doi.org/10.1073/pnas.0307545100

Nijjer S, Singh J, Raj S (2019) Developing HRIS for predictive attrition and retention management of Indian IT engineers-using ANN, ANOVA and Smart PLS.

Nilsson NJ (2005) Human-level artificial intelligence? Be serious! AI Mag 26(4):68–68. https://doi.org/10.1609/aimag.v26i4.1850

Noe R, Hollenbeck J, Gerhart B, Wright P (2006) Human resources management: gaining a competitive advantage, tenth global edition. McGraw-Hill Education, New York, MA

Norikumo S (2019) Changes in organizations due to management mechanization (case studies of life insurance companies in Japan). In: Intelligent decision technologies 2019. Springer, Singapore, pp 249–257. https://doi.org/10.1007/978-981-13-8303-8_22

O'Donovan D (2019) HRM in the organization: AN overview. In: Machado C, Davim J (eds) Management science management and industrial engineering. Springer, Cham, pp 75–110

Oracle (2019) Report of the 2019 state of artificial intelligence in talent acquisition. http://www.oracle.com/a/ocom/docs/artificial-intelligence-in-talent-acquisition.pdf

Otley D (1999) Performance management: a framework for management control systems research. Manag Account Res 10(4):363–382

Petruzzellis S, Licchelli O, Palmisano I, Bavaro V, Palmisano C (2006) Employee profiling in the total reward management. In: International symposium on methodologies for intelligent systems. Springer, Berlin, Heidelberg, pp 739–744

Petruzzellis S, Licchelli O, Palmisano I, Semeraro G, Bavaro V, Palmisano C (2006) Personalized incentive plans through employee profiling. In: ICEIS (2), pp 107–114.

Pillai R, Sivathanu B (2020) Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organizations. Benchmarking Int J 27(9):2599–2629. https://doi.org/10.1108/BIJ-04-2020-0186

Pillai R, Sivathanu B (2021) Measure what matters: descriptive and predictive metrics of HRM-pathway toward organizational performance. Int J Prod Perf Manag. https://doi.org/10.1108/IJPPM-10-2020-0509

Prem E (2019) Artificial intelligence for innovation in Austria. Technol Innov Manag Rev 9(12):5–15. https://doi.org/10.22215/timreview/1287

Quinn A, Rycraft JR, Schoech D (2002) Building a model to predict caseworker and supervisor turnover using a neural network and logistic regression. J Technol Hum Serv 19(4):65–85. https://doi.org/10.1300/J017v19v04_05

Randstad (2020) How will artificial intelligence affect your talent acquisition strategy. https://www.randstad.com/workforce-insights/hr-tech/how-will-artificial-intelligence-affect-your-talent-acquisition-strategy/. Accessed 15 Nov 2020.

Ramos Rodríguez AR, Ruíz Navarro J (2004) Changes in the intellectual structure of strategic management research: a bibliometric study of the Strategic Management Journal, 1980–2000. Strateg Manag J 25(10):981–1004. https://doi.org/10.1002/smj.397

Reddy AJM, Rani R, Chaudhary V (2019) Technology for sustainable HRM: an empirical research of health care sector. Int J Innovative Technol Exploring Eng 9(1):2919–2924

Rich E (1983) Users are individuals: individualising user models. Int J Man Mach Stud 18(3):199–214. https://doi.org/10.1016/S0020-7373(83)80007-8

Salin ED, Winston PH (1992) Machine learning and artificial intelligence: an introduction. Anal Chem 64(1):49A-60A

Sánchez LE, Santos-Olmo A, Álvarez E, Huerta M, Camacho S, Fernández-Medina E (2016) Development of an expert system for the evaluation of students' curricula on the basis of competencies. Future Internet 8(2):22. https://doi.org/10.3390/fi8020022

Sheila LM, Steven G, Chad M, Mayank G (2018) The new age: artificial intelligence for human resource opportunities and functions. Ernst & Young LLP 1–8

Sivathanu B, Pillai R (2019) Technology and talent analytics for talent management—a game-changer for organizational performance. Int J Organ Anal 28(2):457–473. https://doi.org/10.1108/IJOA-01-2019-1634

Srivastava S (2019) Top 10 Countries leading the artificial intelligence race. Analyticsinsight.net. https://www.analyticsinsight.net/top-10-countries-leading-the-artificial-intelligence-race/. Accessed 10 Sept 2021
Small H (2009) Critical thresholds for co-citation clusters and the emergence of the giant component. J Informetr 3(4):332–340. https://doi.org/10.1016/j.joi.2009.05.001
Small H (1973) Co-citation in the scientific literature: a new measure of the relationship between two documents. Wayback machine. J Am Soc Inf Sci 24:265–269. https://doi.org/10.1002/asi.4630240406
Small HG (1980) Co-citation context analysis and the structure of paradigms. J Doc 36:183–196. https://doi.org/10.1108/eb026695
StarMeUp OS (2018) Re: the-power-and-possibilities-of-ai-in-talent-management. https://www.peoplemattersglobal.com/article/learning-technology/the-power-and-possibilities-of-ai-in-talent-management-22418
Stone DL, Deadrick DL, Lukaszewski KM, Johnson R (2015) The influence of technology on the future of human resource management. Hum Resour Manag Rev 25(2):216–231
Strohmeier S, Piazza F (2015) Artificial intelligence techniques in human resource management—a conceptual exploration. In: Intelligent techniques in engineering management. Springer, Cham, pp 149–172. https://doi.org/10.1007/978-3-319-17906-3_7
Strozzi F, Colicchia C, Creazza A, Noè C (2017) Literature review on the 'Smart Factory'concept using bibliometric tools. Int J Prod Res 55(22):6572–6591. https://doi.org/10.1080/00207543.2017.1326643
Stuart R, Norvig P (2016) Artificial intelligence: a modern approach, 3rd edn. Prentice-Hall Press, Upper Saddle River
Suen HY, Hung KE, Lin CL (2020) Intelligent video interview agent used to predict communication skill and perceived personality traits. Human-Centric Comput Inf Sci 10(1):1–12. https://doi.org/10.1186/s13673-020-0208-3
Svensson G (2010) SSCI and its impact factors: a "prisoner's dilemma?" Eur J Mark 44(1/2):23–33. https://doi.org/10.1108/03090561011008583
Tecuci G (2012) Artificial intelligence. Wiley Interdiscip Rev Comput Stat 4(2):168–180
Tranfield D, Denyer D, Smart P (2003) Towards a methodology for developing evidence-informed management knowledge by means of systematic review. Br J Manag 14(3):207–222. https://doi.org/10.1111/1467-8551.00375
Tunger D, Eulerich M (2018) Bibliometric analysis of corporate governance research in German-speaking countries: applying bibliometrics to business research using a custom-made database. Scientometrics 117(3):2041–2059. https://doi.org/10.1007/s11192-018-2919-z
Tursunbayeva A (2019) Human resource technology disruptions and their implications for human resources management in healthcare organizations. BMC Health Serv Res 19(1):268. https://doi.org/10.1186/s12913-019-4068-3
Upadhyay AK, Khandelwal K (2018) Applying artificial intelligence: implications for recruitment. Strateg HR Rev 17(5):255–258. https://doi.org/10.1108/SHR-07-2018-0051
Van Esch P, Black JS, Ferolie J (2019) Marketing AI recruitment: the next phase in job application and selection. Comput Human Behav 90:215–222. https://doi.org/10.1016/j.chb.2018.09.009
Ved S, Kaundanya NS, Panda OP (2016) Applications and current achievements in the field of artificial intelligence. Imp J Interdiscip Res (IJIR) 2(11):932–936
Vinichenko MV, Makushkin SA, Rybakova MV, Chulanova OL, Kuznetsova IV, Lobacheva AS (2019) Using natural and artificial intelligence in the talent management system. Int J Recent Technol Eng 8(3):7417–7423
Vinichenko MV, Chulanova OL, Rybakova MV, Barkov SA, Malyshev MA (2020) The impact of artificial intelligence on behavior of people in the labor market. J Adv Res Dyn Control Syst 12(04):526–532. https://doi.org/10.5373/JARDCS/V12SP4/20201518
Wagner CS, Leydesdorff L (2005) Network structure, self-organization, and the growth of international collaboration in science. Res Policy 34:1608–1618. https://doi.org/10.1016/j.respol.2005.08.002
Wang X (2008) Research on decision support system of employee turnover risk management. In: 38th international conference on computers and industrial engineering, vol 1, pp625–631
Wang X, Wang C (2017) Research on intelligent evaluation system of human resources based on knowledge perspective. Boletin Tecnico/tech Bull 55:656–663
Wu ZX, Nkambou R, Bourdeau J (2012) Cultural intelligence decision support system for business activities. In: The second international conference on business intelligence and technology, BUSTECH.

Xu X, Chen X, Jia F, Brown S, Gong Y, Xu Y (2018) Supply chain finance: a systematic literature review and bibliometric analysis. Int J Prod Econ 204:160–173. https://doi.org/10.1016/j.ijpe.2018.08.003

Yu C, Wang X, Feng Z (2019) Coordinated multiagent reinforcement learning for teams of mobile sensing robots. In: Proceedings of the 18th international conference on autonomous agents and multiagent systems, pp 2297–2299

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. Springer, Cham, pp 265–279. https://doi.org/10.1007/978-3-030-29739-8_12

Zhang H, Yuan W, Jiang H (2012) Performance evaluation on human resource management of China's commercial banks based on improved BP neural networks. Int J Adv Comput Technol 4(11):361–365

Zupic I, Čater T (2015) Bibliometric methods in management and organization. Organ Res Methods 18(3):429–472. https://doi.org/10.1177/1094428114562629

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