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Research article

Artificial intelligence applied to potential assessment and talent identification in an organisational context

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ABSTRACT

Our study provides valuable insights into the relationship between artificial intelligence (AI) and Human Resource Management (HRM). We have minimised bias and ensured reliable findings by employing a systematic literature review and the PRISMA statement. Our comprehensive synthesis of the studies included in this research, along with a bibliometric analysis of articles, journals, indexes, authors' affiliations, citations, keyword co-occurrences, and co-authorship analysis, has produced robust results. The discussion of our findings focuses on critical areas of interest, such as AI and Talent, AI Bias, Ethics and Law, and their impact on Human Resource (HR) management. Our research highlights the recognition by organisations of the importance of talent management in achieving a competitive advantage as higher-level skills become increasingly necessary. Although some HR managers have adopted AI technology for talent acquisition, our study reveals that there is still room for improvement. Our study is in line with previous research that acknowledges the potential for AI to revolutionise HR management and the future of work. Our findings emphasise the need for HR managers to be proactive in embracing technology and bridging the technological, human, societal, and governmental gaps. Our study contributes to the growing body of AI and HR management knowledge, providing essential insights and recommendations for future research. The importance of our study lies in its focus on the role of HR in promoting the benefits of AI-based applications, thereby creating a larger body of knowledge from an organisational perspective.

1. Introduction

The Peter Principle, as defined in the Peter Principle of Management [1], states that "*every employee tends to rise to his level of incompetence*", meaning that the best employees are not always the best candidates for promotion. The Peter Principle states that promotion decisions often support the candidate's performance in current roles rather than necessarily their capacity to perform in long-term management roles. It also demonstrates that, even if an employee's tasks change, organisations continue to believe that the attributes that have made someone successful in the past will continue to contribute to their success in the future. According to Bersin

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& Chamorro-Premuzic [2], individuals are promoted based on past achievements.

Understanding the importance of hiring the right person has become a priority for many businesses [3]. While talent management encompasses various human resource strategies, Claussen et al. [4] argue that strategic talent management covers an organisation's identification of essential jobs and, later, the building of a talent pool to fill these positions. According to this definition, necessary position staffing is a critical component of talent management [4]. Organisations that efficiently manage their human capital are more likely to achieve outstanding performance and generate long-term competitive advantage [5–7]. A breakthrough McKinsey report published in 1997 [8] identified the "war for talent" as a strategic business problem and a significant driver of company success. Even when many people thought the struggle for talent was over, it was not. According to the authors [8], the battle for talent would continue for the next two decades due to persisting economic and societal causes, revealing that winning the fight for leadership talent requires much more than disruptive recruitment methods. It shows the pressing need for more about using time-tested concepts of attracting, developing, and keeping highly competent managers in daring new ways. Talent management ties directly to the notion of enterprise management and knowledge transfer. When seen through the lens of international corporations as a way of obtaining success, this issue takes on additional significance [7].

Although definitions concerning talent differ, four essential criteria separate more talented people from less qualified employees [9]. The first is the 80/20 rule, based on Vilfredo Pareto's observation [10] that a small number of people produce a disproportionate percentage of any group's production. Specifically, about 20% of employees will account for around 80% of productivity. The second is the concept of maximum performance, which equates talent with the most an individual can achieve as their highest possible performance. The third associates talent with seamless achievement, emphasising the importance of natural ability or potential, meaning a more talented person will outperform a less capable person. The fourth connects skill and personality in the proper context, as individuals should perform at a greater level when their talents match a task. According to Chamorro-Premuzic et al. [9], these criteria can classify individuals as more or less gifted.

Even though it is possible to win the talent battle [11], an organisation must make talent management a top business priority. Therefore, the organisation must constantly develop and improve the employee value proposition to recruit and retain the right individuals. In essence, the war for talent is about understanding the strategic relevance of human capital due to the significant value that more excellent skills provides [7,8]. An organisation's workforce can provide the talent it needs, which aligns with its goals and strategy. Conducting talent management processes aimed at an organisation's employees is critical, as organisational talent is, in the long run, one of the most vital components in transforming crises into organisational success [12]. According to Coates [13], performance appraisals are part of the postmodern corporate concept of a human-centred, subjective management system intended to uncover potential in employees and motivate and reward them. One of the most critical aspects of performance management, according to Mert [14], is defining what "good performance" means. In recent years, the notion of effective performance has shifted away from dependent activities towards creativity, innovation and elements that diminish employee interdependence. Assessing these characteristics demands an evaluation of employees' potential for future success [14].

According to Assessment Associates International [15], organisations must evaluate candidates on two primary criteria to determine talent: performance (an individual's efficacy and outcomes in their current role) and potential (the anticipated future performance of an individual if they have development opportunities and greater responsibility). Although performance evaluation helps an organisation evaluate its employees' performance, it only provides limited information on potential performance in areas that demand different skills, according to Künneke [16]. Moreover, the purpose of potential assessment is to manage future performance, which means that it goes beyond evaluating an employee's past and present behaviour to identify the employee's potential performance, which links to the latent qualities that the employee possesses but has not yet been made available to the organisation [14].

Potential in an organisational context refers to an individual's ability to advance and succeed in a higher position, that is, to grow and deal with more responsibilities and scope [17]. By assessing their employees' potential, organisations obtain the essential knowledge to set realistic goals based on the capabilities of their teams, preventing dissatisfaction and bad performance scenarios. Strategies define capabilities, and capabilities represent talent [18].

Künneke [16] asserts it is critical to discern between high potential and high performers. High potentials can handle confusing and challenging tasks, making them good candidates for senior and leadership roles in the organisation. High performers have in-depth knowledge of their expertise and outperform their counterparts in their present employment. On the other hand, high potentials adapt quickly to new activities and environments, excelling even in areas outside their current work and specialisation. In the 1970s, McKinsey [19] created the Nine Box Matrix to assist General Electric in prioritising investments across its 150 business divisions. The matrix assessed each business unit's industry attractiveness and competitive strength. Not every business unit was equally appealing. It was ascertained that some should be invested in, while others should be extinguished. HR teams have adopted this model as a talent management tool over the last 40 years, replacing the two industrial axes with people-specific ones: performance and potential. The main goal of the Nine Box Matrix is to categorise employees, determine which to promote, retain and invest in, and which to reallocate. Companies give the few employees that strongly influence the company's performance particular attention through individualised and tailored solutions with higher aspirations and expectations to match the increased investment in them [18].

Additionally, three trends in the Hype Cycle for Human Capital Management Technology in 2021 can be observed, as noted by Zuech [20]. Because of the fierce competition for talent and the expanding number of job openings, talent acquisition leaders are working harder to get applicants through the pipeline [20]. As a result, AI in talent acquisition (TA) and video recruiting are two breakthroughs helping to ease some of these pain points to fill openings more swiftly and efficiently as the first trend. The second trend is using technology to develop and retain talent, as employee interactions and career advancement facilitate the internal talent marketplace and Learning Experience Platforms (LEPs). The third trend is regarding technology related to employee well-being and productivity.

Likewise, we can analyse the Hype Cycle for Artificial Intelligence in 2021 and observe four emerging trends, as detailed by Goasduff [21]. Organisations are rapidly embracing AI solutions to innovate and improve existing products by leveraging Natural Language Processing (NLP) and upcoming technologies such as generative AI, knowledge graphs and composite AI. As a result, the four trends that dominated 2021's AI landscape are 1) Implementing AI projects; 2) Making efficient use of data, models, and computing; 3) Data for AI and 4) Responsible AI.

AI is considered a game-changer since it can provide self-learning capabilities as well as increase decision quality [22], and still, both Jia [23] and Tambe [24] state that there is a gap between the promise and the reality of AI technology application in the Human Resources Management field.

There is a research gap for more technological models concerning implementing AI technologies in HRM across organisations [24–26]. We need more progress regarding what concerns HRM when algorithms make choices, mainly because of the complexity of the human resources phenomena, data issues from human resources processes, fairness and legal restrictions, and employee engagement in AI management.

1.1. Research problem

According to Chamorro-Premuzic et al. [9], the digital revolution has resulted in many new technologies that quickly and cheaply infer human potential and forecast future work performance. However, academic Industrial–Organisational (I–O) psychologists, who focus on the behaviour of employees in the workplace, appear to be mere observers, as there has been sparse scientific research on new evaluation methods, leaving HR practitioners with little solid data to judge the effectiveness of such tools.

Additionally, AI as a game-changing technology will revolutionise the workplace, but it is still in its infancy in HR and people management [27]. There is a relentless quest for talent which means there is a need to find and retain talent inside organisations, so organisations should invest in talent management to attract top talent, motivate their employees and ensure essential tasks at all times [28]. Furthermore, improving the efficiency of Human Resource Management through AI has become an important trend in the future development of Human Resource Management [29]. However, only 22% of organisations claim to have implemented analytics in HR, and we need to clarify how sophisticated those analytics are in those organisations [24].

As such, AI technology and human capital, as well as AI's importance to human capital-related performance, are still in early development [30], and AI is crucial in improving the quality of HR choices [31]. We expect AI to revolutionise and enhance the human resources industry [32], and AI research's theoretical and practical significance in HRM has been proven [33]. Although recent studies have discovered more than 300 Human Resources technology start-ups developing AI tools and products for HR or people management, with almost 60 of these organisations attracting customers and funding, there is minimal information on the application and impact of Machine Learning (ML) in HR [27]. AI might bring a future of significant increases in fairness and efficiency. However, it can also evolve into pervasive injustice and abusive control over managers' decisions, implying that both scenarios can coexist [34]. Although adopting AI systems in organisations is still restricted [35], an AI-driven future is rapidly dawning [27]. This phenomenon prompts a more significant concern regarding the implications of the lack of ethics and resulting injustices of the use of AI in Human Resources, potentially leading to a corporate control future, reflecting internal criticisms of the technology sector, which states that AI engineers are excessively focused on technical problems and financial goals while ignoring the ethical and societal implications of their work [36].

Modern organisations must support their operations in information systems to survive the talent war. AI in HR activities is one conceivable architecture that will demand a more profound transformation to address the evolution of the old HR processes into more valuable methods improved by information technologies. In this perspective, many new challenges are posed to both organisations and information systems, making it essential to have methodologies to support these changes, particularly if the existing ones do not meet the requirements. The existence of a framework or model that allows a systematic approach to all these questions, enabling organisations to use it to support their employee's talent towards this paradigm, is of great interest and practical utility in our opinion, and the directions and answers should be discussed and found.

An AI-based model can assist and improve HRM's goal of analysing its employees' potential. As such, research that can accomplish it will add value to the scientific community and all organisations, giving them a competitive advantage.

1.2. Study relevance and importance

In today's corporate world, we primarily determine success by having the right people to execute the strategy. Organisations that invest in talent acquisition methods will win [28]. According to Thomas, one of the most important reasons to identify High Potential employees (HiPo) is to find people who will become successful professionals within the organisation [37]. Identifying suitable candidates will justify more significant investment in their development, shaping, and making them future leaders of the organisation.

Furthermore, according to Ready, in a Harvard Business Review analysis [38], organisations recognise special qualities in over 5% of their high-potential employees, such as how they consistently outperform their peers in a variety of situations, demonstrating exemplary actions that represent the culture and values of their organisations by achieving these superior levels of performance.

As such, high-potential employees demonstrate a significant ability to grow and succeed more quickly and efficiently than their colleagues throughout their careers. The most important decision a manager can make is hiring the right individual. If we place the wrong individual in the wrong position, a thoroughly planned strategy is as harmful as having no strategy [39].

Business executives understand the value of and scarcity of talent [28]. A staggering 82% of Fortune 500 companies do not believe they hire highly talented employees. Moreover, when top talent becomes rarer, organisations that need to be better to compete will find their finest employees cherry-picked by those who are. Top talent will become more infrequent as millennials are significantly less devoted to their companies than their parents were.

Even though people analytics is still in its infancy, it is gaining traction. Leaders who need to implement actual plans to use technology to help them compete for talent will swiftly stay caught up [28]. AI is in a good place right now, thanks to significant improvements in computers' computing power and access to massive amounts of data [40]. According to Brynjolfsson [41], AI, especially ML, is the most important general-purpose technology of our era, that is, to maintain its capacity to improve performance without having to explain precisely how to carry out all the tasks. Big Data concerns large amounts of data involving volume, velocity and variety [42]. In that sense, we will need significant amounts of data, as data is one of the essential resources for a company to achieve competitive performance.

An increase in AI has substantially impacted operations and human roles in businesses in the manufacturing and supply chain management sectors, showing that AI initiatives in the Industry 4.0 landscape can enhance understanding of the processes that lead to business performance [22]. From an industrial point of view, according to Peres et al. [43], AI technologies may be considered enablers for systems to improve their ability to do specific tasks, perceive their environment, analyse data collected, and solve complex problems, as well as learn from experience.

As such, AI provides new opportunities for organisations seeking to solve management challenges through new means [44]. Organisations can benefit significantly by using machines or systems that make this process more exact and less biased [45]. Large multinational technology corporations have also begun integrating AI into their people management systems and procedures. IBM estimated the cost savings from applying artificial intelligence in human resources approached $100 million in a year [27].

2. Data and methods

It was necessary to build a theoretical framework to better understand better the work done on the topics under study and what concepts are required to explore to start working on applying AI to the assessment of potential and talent identification. A systematic review aims to collect all empirical data that meets pre-specified qualifying criteria to answer a research issue. It employs routine techniques to minimise bias, resulting in reliable findings from which inferences and judgments can be drawn [46].

2.1. Systematic literature review methodology

The aim is to present a correct assessment of the research topic using a reliable, rigorous and auditable methodology, so we conducted a thorough and methodical Systematic Literature Review (SLR), adopting the "Preferred Reporting Items for Systematic Reviews and Meta-Analysis" (PRISMA) statement [47] to find out what knowledge exists about the subjects of this study and its associated concepts, to explore and acknowledge the literature available and obtain the knowledge that we believe is relevant and will sustain this research, as well as to support the previously mentioned research questions. As a result, the systematic review described in this section adhered to the PRISMA methodology's standards and instructions.

The purpose of this study is to be able to answer the following research questions: RQ1) How can AI models be used to evaluate employee potential? RQ2) How effective are AI models in talent identification? RQ3) How do AI models bias talent identification?

2.2. Study limitations

The electronic databases used during the SLR are one area of the study over which the author has limited influence. Because these computerised resources deliver results automatically, there needs to be more control over what they return. It may result in no two searches being genuinely similar, influencing future studies' ability to duplicate the study undertaken precisely. We have made several decisions during the protocol development which may impact the SLR's outcomes. Individual interpretations may impact the inclusion, exclusion, and study selection criteria and the data extraction approach, meaning that what one researcher included, another may have excluded. We intended to minimise the subjectivity of the selection of the included studies by providing a quantitative approach to the method of selection through a quality assessment of all eligible articles.

2.3. Literature search

We divided our literature search into two parts: an initial exploratory search and a more systematised search. Since we are interested in analysing the application of artificial intelligence in HR or employee potential and talent in an organisational environment, we conducted a preliminary inquiry to find relevant literature and keywords for our study subject. We needed to figure out

Table 1
Keywords found during the snowballing process.

Keywords			
Artificial intelligence	Potential assessment	Talent	High-potentials
Human	Resources	Capital	Personnel management
Evaluation	Quality	Assessment	Human resource
Potential	Human resources management	Employee	Human capital

the right keyword formula to identify relevant articles. To do so, we conducted a preliminary scoping search of relevant publications to uncover term usage trends. According to Wholin [48], this technique should start with identifying a starting group of papers to apply the snowballing process. Any search for articles to include in the start set returns an initial set we might have in the systematic literature analysis at the end. One possibility for snowballing is to find highly referenced work in the field of systematic literature review. This procedure discovered several keywords, as seen in Table 1, including the keywords used to create our search query. Bates [49] refers to these keywords as “entry terms”. They will be the foundation for our more structured literature search and review.

We created a single search algorithm using conventional boolean operators [50]. We designed these logical parameters to include all the studies and publications deemed most relevant for this research. As a result, to identify the publications to be analysed through using the PRISMA methodology, the following query was written and executed to search for articles that were published and contained at least (OR logical operator) one of the following terms/expressions in their title, resume, abstract, or full-text or keywords: “employee”, “human capital”, “human resource”, “personnel management”, “talent”. These keywords were paired with the Boolean operators “OR” and “AND”, obtaining the following query *(employee **OR** human capital **OR** human resource **OR** personnel management **OR** talent) **AND** “artificial intelligence”*.

We ran this query on the EBSCOhost interface (EBSCO aggregates nearly 400 research databases) during March 2022 using their powerful search engine to search over the following databases: EBSCO Academic Search Complete; EBSCO Business Source Complete; ERIC; EBSCO Library, Information Science & Technology Abstracts (LISTA); and Regional Business News. The decision to use these databases is anchored in the observation that research related to technological advancements and HRM is mainly published in journals covered by EBSCO databases, as listed before, according to Vrontis et al. [31], providing a representative sample of the interdisciplinary literature on the topics under study. This resource offers a quick and easy way to search academic literature across multiple disciplines *and databases*. EBSCO aggregates nearly 400 research databases. As a result, the number of records collected from the EBSCOhost interface provided 5072 results in this first stage.

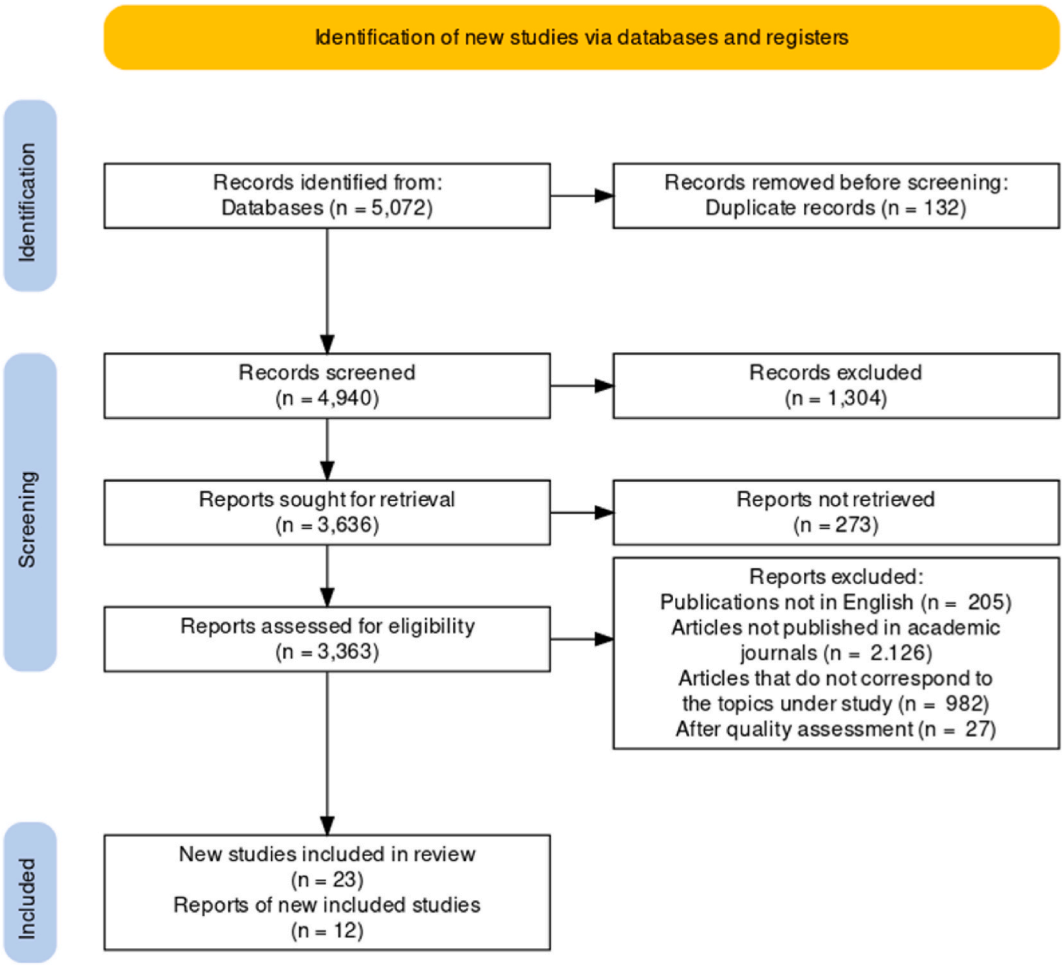

Fig. 1. PRISMA data flow diagram for the Systematic Literature Review.

2.4. Screening and eligibility

We reviewed all studies discovered in the first stage for eligibility using exclusion criteria, as PRISMA recommends. We evaluated this to ensure that each article met specific requirements and addressed the research question. According to Awan et al. [51], criteria for inclusion or exclusion provide substantial justification for the validity of the selected studies. Logic and reason are the foundations of the inclusion or exclusion criteria, with important implications for the outcomes and conclusions. The criteria for exclusion were as follows: 1) Articles not available in full text. The exclusion criterion for articles not available in full text is self-explanatory, as access to the entire article is necessary to understand it. 2) Eliminating articles written before 2010. The exclusion criterion for articles written before 2010 was that this study focuses on AI and organisational issues like potential and talent, which are constantly evolving subjects. Therefore, the relevant studies are those that have been more recently published. There is an undeniable indicator of the recent (10-year) tremendous rise in AI research in the Big Data age [52]. 3) Articles not written in English. The exclusion criterion for articles not written in English might exclude essential studies. However, we accept English as the universal language for academic studies, meaning we will find all relevant published studies this way. 4) Articles not published in academic journals. The exclusion criterion for articles not published in academic journals is an intention to only focus on the most successful studies published, as the peer-review method maintains academic scientific excellence by subjecting an author's scholarly work, research, or ideas to the examination of those who are experts in the same area. Even not including peer-reviewed conference publications was a choice, as per our experience, conference publications tend to become articles in academic journals. The dataset included all the results obtained after successfully applying the exclusion criteria.

As a result of our search, we obtained 5.072 results. We exported all the retrieved documents to Zotero, a reference insertion tool for duplication checks and removing duplicate entries. This check eliminated 132 papers leading to a sample of 4.940 documents that were not duplicates. When excluding articles by not being in full text, we removed 1.304 articles, leaving 3.636 results. Again, when excluding articles published before 2010, 273 articles were removed, which led to a sample of 3.363 results. While excluding articles not written in English, we removed 205, leaving a total of 3.158 results. When excluding articles not published in academic journals, we removed 2.126, leaving 1.032 results. We ended with 1.032 articles to evaluate. Of these 1.032 articles, we excluded 982 after reading the title and abstract because those articles did not correspond to the topic under study, leaving 50 articles eligible for a full reading. In addition to the documents collected through this protocol, we also identified extra articles, either because they were references used in the papers researched or because they were the result of independent research on the topics in question. We found those using Google Scholar. In this manner, we identified 12 articles assessed for eligibility. We ended up with 62 articles eligible for evaluation through full reading, as seen in Fig. 1.

2.5. Included studies

We conducted a quality assessment of these 62 articles. We have used the following questions to guide the selection of articles to include in this study:

1. Is the article relevant to answer the question of the present study?
2. Does the article focus on AI and talent as the subject of the study?
3. Does the article focus on AI and human resource management as the subject of the study?
4. Does the article focus on AI and bias regarding human resources as the subject of the study?

Note that all articles have merit and quality. That is not the point. The quality evaluation approach will occur concurrently with the extraction of pertinent data to guarantee that a specific study's findings will make a valuable addition to the SLR. As Joshi [53] states, the research goal informs the creation of the Likert scale. Certain studies aim to learn about the participants' beliefs and perceptions of a single latent variable (a variable that cannot be observed) or phenomenon of interest. Several manifested items in the questionnaire express this latent characteristic. These built pieces target a specific facet of the subject under investigation and, in coherence, quantify the entire phenomenon. Adding all the questionnaire's values during analysis produces a composite score, which logically assesses a single-dimensional characteristic. Following Likert scale parameters, we rated the answers to the questions to "Strongly Agree", "Agree", "Neutral", "Disagree", and "Strongly Disagree", each receiving a score, as shown in Table 2, determining the final inclusion/exclusion of documents in the study.

The maximum score is calculated based on the number of questions and the answer of greater weight, and the minimum score for selecting an article was set at 3.5, as seen in Table 3. There are articles where the content needs to answer all the questions but is still relevant enough to be included. Therefore, while determining the minimum score for inclusion, the article should have at least three answers with "Strongly Agree", "Agree", and "Neutral". From these 62 articles, we excluded 27 after full reading, so 35 studies were included in the systematic review.

Table 2
Score for each answer to questions on the quality assessment list.

Answer	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
Score	2.0	1.0	0.5	0.0	0.0

Table 3
Quality assessment scores.

Scores	
Maximum score	8.0
Cutoff score	3.5

Technology research-enabled HRM has covered a variety of themes in a variety of contexts. Hence the concerns addressed in the reviewed papers are broad. We looked for similar themes across the articles to group them into research themes based on the unit of analysis to answer our research questions, as described in Table 4.

As a result, we categorised the publications into these study themes: "AI & Talent", "AI & Human Resource Management", and "AI Bias, Ethics and Law", as seen in Table 4. The Bibliographical matrix can be seen in Table 5, arranged by year, descending.

2.6. Bibliometric analysis

According to Donthu et al. [82], bibliometric analysis is a common and rigorous approach for examining and interpreting vast amounts of scientific data, allowing us to explore the evolutionary subtleties of a particular discipline while also shedding light on new topics in that field. For this study, we chose the VOSviewer tool, a text mining application for network and map analysis, to perform the citation analysis, the co-authorship analysis, and the co-word analysis. For other bibliometric data analysis, we used Google Sheets to create charts based on the data recovered from the Scimago website for article count, journals, and author's affiliate data. Table 6 shows the overall dataset with the respective quartiles, h-index and SJR scores.

2.6.1. Article data analysis

We can observe the published year for the 35 included articles in the following order: 4 in 2022, 15 in 2021, 8 in 2020, 4 in 2019, 2 in 2018, 1 in 2017, and 1 in 2015.

As shown in Fig. 2, 42, 85% of the articles were published in 2021. Furthermore, 77,15% of the included articles were published in 2022, 2021 and 2020, with 27 articles, as depicted in Fig. 3.

2.6.2. Journal data analysis

New publication strategies and rising pressure on academics are pushing these developments to publish in high-ranking journals. According to Rowley et al. [83], the number of journals has increased significantly, as have changes in the coverage and status of established journals, making it difficult for even experienced scholars to make article selection decisions. According to Liu et al. [84], quartile journals denote a journal's impact factor along the 100% scale of the JIF distribution of a particular category, broken into four quartiles starting with Q1, Q2, Q3, and Q4. Table 7 shows the list of journals from the overall dataset, arranged alphabetically per quartile.

Twenty articles were published in Q1 journals, 4 in Q2 journals, three in Q4 journals, and eight in non-quartile journals, as depicted in Fig. 4. The listed journals belong to Q1, Q2 and Q4. Seven of the journals do not belong to a quartile.

77,1% of the articles were published in quartiles with 27 articles, as depicted in Fig. 5. We can observe the number of articles published per journal from the overall dataset in Fig. 6.

2.6.3. Journal indexes

According to Gonzalez-Pereira et al. [85], citation analyses are critical elements of research assessment systems. Rowley et al. [83] add that journal rating has also grown in importance. There are more than 300,000 scientific publications in the world now, according to Ulrich's Periodicals Directory [86]. However, 270,000 are not subject to peer review, implying that just 30,000 journals should be considered seriously. Journal Citation Reports (JCR), presently administered by Clarivate Analytics, has supplied a journal rating service since 1955. Researchers have traditionally shared conceptions about their discipline's 'most highly rated' publications [83]. An academic journal's impact factor (IF) or journal impact factor (JIF) is a scientometric indicator developed by Clarivate that indicates the yearly mean number of citations of papers published in the previous two years in a particular journal, as indexed by Clarivate's Web of Science (WoS) [87].

The SCImago Journal Rank index (SJR) is a measure of a journal's scientific influence that considers both the number of citations

Table 4
References by the theme and research questions.

Theme	References
AI & Talent RQ1) How can AI models be used to evaluate employee potential?	[23–27,31,39,54–73]
AI & HRM RQ2) How effective are AI models in talent identification?	[23–27,31,39,54–81]
AI Bias, Ethics and Law RQ3) How do AI models bias talent identification?	[24,27,54,60,68,74–76,78–81]

Table 5
Bibliographical matrix arranged by year, descending.

Article Title	References	Theme	Year	Score
Artificial intelligence, robotics, advanced technologies and human resource management: a systematic review.	[31]	AI & Talent; AI & HRM	2022	4.0
AI Predicted Competency Model to Maximise Job Performance.	[39]	AI & Talent; AI & HRM	2022	6.0
Ethics of AI-Enabled Recruiting and Selection: A Review and Research Agenda.	[54]	AI & Talent; AI & HRM; AI Bias, Ethics and Law	2022	7.0
Can HR adapt to the paradoxes of artificial intelligence?	[27]	AI & Talent; AI & HRM; AI Bias, Ethics and Law	2022	8.0
Legal and Ethical Challenges for HR in Machine Learning.	[74]	AI & HRM; AI Bias, Ethics and Law	2021	4.5
Legal perspective on possible fairness measures – A legal discussion using the example of hiring decisions.	[75]	AI & HRM; AI Bias, Ethics and Law	2021	4.5
Adoption of Artificial Intelligence in Human Resource Management: A Conceptual Model.	[25]	AI & Talent; AI & HRM	2021	4.5
Measurement of Employees on Human Resources with Fuzzy Logic.	[55]	AI & Talent; AI & HRM	2021	4.0
Artificial Intelligence and the Challenges of Workplace Discrimination and Privacy.	[76]	AI & HRM; AI Bias, Ethics and Law	2021	6.5
HR Analytics and Artificial Intelligence-Transforming Human Resource Management.	[56]	AI & Talent; AI & HRM	2021	5.5
Digitalised talent management and automated talent decisions: the implications for HR professionals.	[57]	AI & Talent; AI & HRM	2021	4.5
Analysis of Talent Management in the Artificial Intelligence Era.	[58]	AI & Talent; AI & HRM	2021	6.5
AI-enabled recruiting in the war for talent.	[59]	AI & Talent; AI & HRM	2021	5.5
Disrupted HR?	[77]	AI & HRM;	2021	4.0
Will AI ever sit at the C-suite table? The future of senior leadership.	[60]	AI & Talent; AI & HRM; AI Bias, Ethics and Law	2021	6.0
When The Machine Meets The Expert: An Ethnography Of Developing Ai For Hiring.	[61]	AI & Talent; AI & HRM	2021	4.5
The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions.	[62]	AI & Talent; AI & HRM	2021	5.0
A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective.	[63]	AI & Talent; AI & HRM	2021	5.5
Algorithmic human resource management: Synthesising developments and cross-disciplinary insights on digital HRM.	[64]	AI & Talent; AI & HRM	2021	4.5
Designing fair AI for managing employees in organisations: a review, critique, and design agenda.	[78]	AI & HRM; AI Bias, Ethics and Law	2020	5.5
An analysis of the literature about the application of Artificial Intelligence to the Recruitment and Personnel Selection.	[65]	AI & Talent; AI & HRM	2020	4.5
A Novel Fuzzy Scoring Approach of Behavioural Interviews in Personnel Selection.	[66]	AI & Talent; AI & HRM	2020	5.0
Industrial human resource management optimization based on skills and characteristics.	[67]	AI & Talent; AI & HRM	2020	5.5
Justice perceptions of artificial intelligence in selection.	[79]	AI & HRM; AI Bias, Ethics and Law	2020	4.5
Machine learning and human capital complementarities: Experimental evidence on bias mitigation.	[80]	AI & HRM; AI Bias, Ethics and Law	2020	6.5
Adoption of artificial intelligence (AI) for talent acquisition in IT/IteS organisations.	[26]	AI & Talent; AI & HRM	2020	5.5
A framework for fairer Machine Learning in organisations.	[68]	AI & Talent; AI & HRM; AI Bias, Ethics and Law	2020	6.0
Absolute answerability in the Era of Artificial Intelligence and Machine Learning: A talent management perspective.	[69]	AI & Talent; AI & HRM	2019	5.5
Classification Talent of Employee Using C4.5, KNN, SVM.	[70]	AI & Talent; AI & HRM	2019	5.5
What do we lose when machines take the decisions?	[81]	AI & HRM; AI Bias, Ethics and Law	2019	4.5
Artificial intelligence in human resources management: Challenges and a path forward.	[24]	AI & Talent; AI & HRM; AI Bias, Ethics and Law	2019	6.0
Can artificial neural networks predict lawyers' performance rankings?	[71]	AI & Talent; AI & HRM	2018	6.5
A conceptual artificial intelligence application framework in human resource management.	[23]	AI & Talent; AI & HRM	2018	5.5
The datafication of talent: How technology is advancing the science of human potential at work.	[72]	AI & Talent; AI & HRM	2017	5.0
Talent management in the manufacturing system using a fuzzy logic approach.	[73]	AI & Talent; AI & HRM	2015	6.5

received and the importance or prestige of the journals from which such citations are obtained [87]. The Impact Factor (IF) (official Thomson-Reuters score) and the SJR (SCImago Journal Rank) differ in that the former is based on the ISI Web of Science database and the latter on the Scopus database. Scopus, Elsevier's abstract and citation database, was established in 2004 and incorporated the h-index metrics, which reflects the most excellent value of h such that the particular journal has published at least h papers, each of which has been referenced at least h times [87].

Furthermore, article citations are an indirect indicator of quality, and it is widely considered that both Impact Factor (IF) and Citations/Document (C/D) reflect quality, as stated by Rocha-e-Silva [86]. Journals with a high IF or C/D are ideal for publishing scientific findings because most meaningful scientific results are published in high-impact journals. However, there is no evidence to prove it, despite popular belief.

According to Hirsch [88], the h-index is valuable for measuring a researcher's scientific output. Bornmann [89] states that what determines Hirsch's h-index is the number of publications a scientist has and the effect of those publications on the scientist's peers. According to Guerrero-Bote et al. [90], the SCImago Journal Rank (SJR) indicator measures a journal's influence. It indicates the average number of weighted citations obtained in the chosen year by papers published in the journal in the preceding three years. The

Table 6
Bibliometric data for the overall dataset.

Article Title	Quartile	h-index	SJR
Artificial intelligence, robotics, advanced technologies, and human resource management: a systematic review.	Q1	123	1.54
AI Predicted Competency Model to Maximise Job Performance.	Q2	41	0.56
Ethics of AI-Enabled Recruiting and Selection: A Review and Research Agenda.	Q1	208	2.44
Can HR adapt to the paradoxes of artificial intelligence?	Q1	82	2.50
Legal and Ethical Challenges for HR in Machine Learning.	Q4	33	0.22
A legal perspective on possible fairness measures – A legal discussion using the example of hiring decisions.	Q1	41	1.14
Adoption of Artificial Intelligence in Human Resource Management: A Conceptual Model.	n.a.	n.a.	n.a.
Measurement of Employees on Human Resources with Fuzzy Logic.	n.a.	n.a.	n.a.
Artificial Intelligence and the Challenges of Workplace Discrimination and Privacy.	Q4	8	0.10
HR Analytics and Artificial Intelligence-Transforming Human Resource Management.	n.a.	n.a.	n.a.
Digitalised talent management and automated talent decisions: the implications for HR professionals.	Q1	123	1.54
Analysis of Talent Management in the Artificial Intelligence Era.	n.a.	n.a.	n.a.
AI-enabled recruiting in the war for talent.	Q1	97	2.38
Disrupted HR?	Q1	101	2.84
Will AI ever sit at the C-suite table? The future of senior leadership.	Q1	97	2.38
When The Machine Meets The Expert: An Ethnography Of Developing Ai For Hiring.	Q1	243	4.50
The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions.	Q1	132	4.58
A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective.	Q1	101	2.84
Algorithmic human resource management: Synthesising developments and cross-disciplinary insights on digital HRM.	Q1	123	1.54
Designing fair AI for managing employees in organisations: a review, critique, and design agenda.	Q2	73	0.69
An analysis of the literature about the application of Artificial Intelligence to Recruitment and Personnel Selection.	Q4	9	0.23
A Novel Fuzzy Scoring Approach of Behavioural Interviews in Personnel Selection.	n.a.	n.a.	n.a.
Industrial human resource management optimization based on skills and characteristics.	Q1	136	1.78
Justice perceptions of artificial intelligence in selection.	Q1	66	0.82
Machine learning and human capital complementarities: Experimental evidence on bias mitigation.	Q1	300	9.44
Adoption of artificial intelligence (AI) for talent acquisition in IT/IteS organisations.	Q1	66	0.89
A framework for fairer Machine Learning in organisations.	Q1	336	10.87
Absolute answerability in the Era of Artificial Intelligence and Machine Learning: A talent management perspective.	n.a.	n.a.	n.a.
Classification Talent of Employee Using C4.5, KNN, SVM.	n.a.	n.a.	n.a.
What do we lose when machines take the decisions?	Q2	53	0.58
Artificial intelligence in human resources management: Challenges and a path forward.	Q1	139	3.79
Can artificial neural networks predict lawyers' performance rankings?	Q2	67	0.58
A conceptual artificial intelligence application framework in human resource management.	n.a.	n.a.	n.a.
The datafication of talent: How technology is advancing the science of human potential at work.	Q1	53	1.66
Talent management in the manufacturing system using a fuzzy logic approach.	Q1	163	1.78

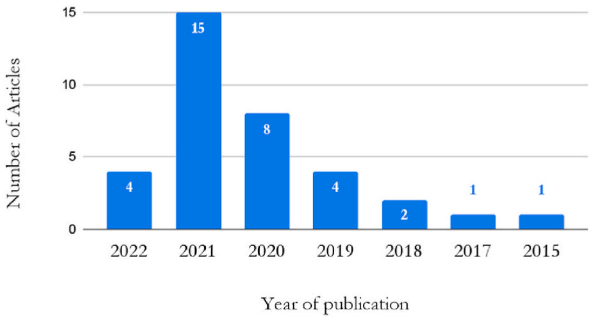

Fig. 2. Number of articles per year of publication.

SJR indicator is derived from the well-known Google PageRank algorithm and depicts the visibility of journals in the Scopus database from 1996. From the 35 included articles, eight articles did not have any SJR, or h-index score attributed, so the overall dataset for this analysis is 27 articles, as seen in Fig. 7.

From the overall dataset, we can observe that the majority (55%) of the h-index values are below 100, while the other articles (45%) are above 100. Regarding those 27 articles, only 18% are below 50, as depicted in Fig. 8.

From the overall dataset, regarding the SJR index, we can observe that the minority (40%) of the SJR values are above 2, with the remaining articles (60%) below 2. From the total, 18% of the articles are above 3, and 7% are above 9, as depicted in Fig. 9. Observing both h-index and SJR values, we can understand that higher h-index values can also translate to higher SJR values, as illustrated in Fig. 10.

Correlation coefficients indicate how closely two variables are related to one another. Correlation between two variables means that changes in one variable are related to changes in the other. Furthermore, Fig. 11 shows a highly significant correlation (R^2 = 0.789) between h-index and SJR values.

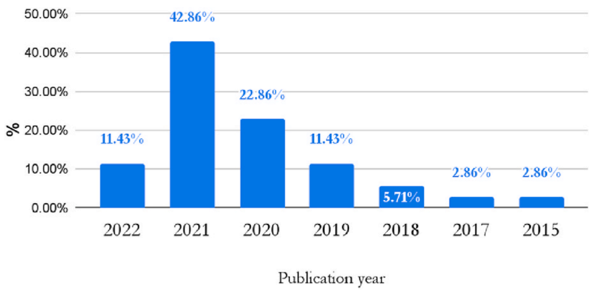

Fig. 3. % of articles per year of publication.

Table 7
Journal list arranged alphabetically per quartile, descending.

#	Journal	Quartile
1	Academy of Management	Q1
2	Benchmarking	Q1
3	Business Horizons	Q1
4	California Management Review	Q1
5	Computer Law and Security Review	Q1
6	Computers and Industrial Engineering	Q1
7	Current Opinion in Behavioural Sciences	Q1
8	Human Resource Management Journal	Q1
9	Human Resource Management Review	Q1
10	International Journal of Human Resource Management	Q1
11	International Journal of Information Management	Q1
12	International Journal of Selection and Assessment	Q1
13	Journal of Business Ethics	Q1
14	MIS Quarterly: Management Information Systems	Q1
15	Strategic Management Journal	Q1
16	Cybernetics and Systems	Q2
17	Human–Computer Interaction	Q2
18	International Journal of Productivity and Performance Management	Q2
19	Journal of Management and Governance	Q2
20	Applied Psychology Bulletin	Q4
21	Employee Responsibilities and Rights Journal	Q4
22	Journal of Labor and Employment Law	Q4
23	2019 International Conference on Digitization	n.a.
24	2019 International Conference on Information and Communications Technology	n.a.
25	2021 International Conference on Decision Aid Sciences and Application	n.a.
26	Advances in Economics, Business and Management Research	n.a.
27	BRAIN. Broad Research in Artificial Intelligence and Neuroscience	n.a.
28	Emerging Markets Journal	n.a.
29	International Conference on Electronic Business	n.a.

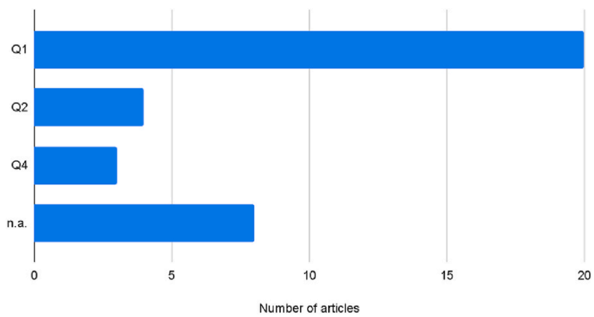

Fig. 4. Count of articles per quartiles.

2.6.4. Authors' affiliation data analysis

To date, bibliometric analyses of computer science and database publications have mainly concentrated on the number of articles and citations per author or journal. Because bibliographic systems focus on journals, there is a minimal analysis of author affiliations in

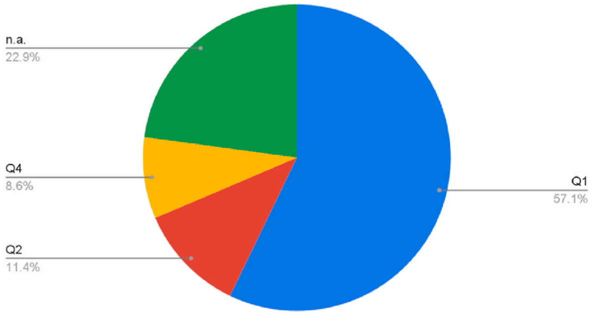

Fig. 5. % of articles per quartile.

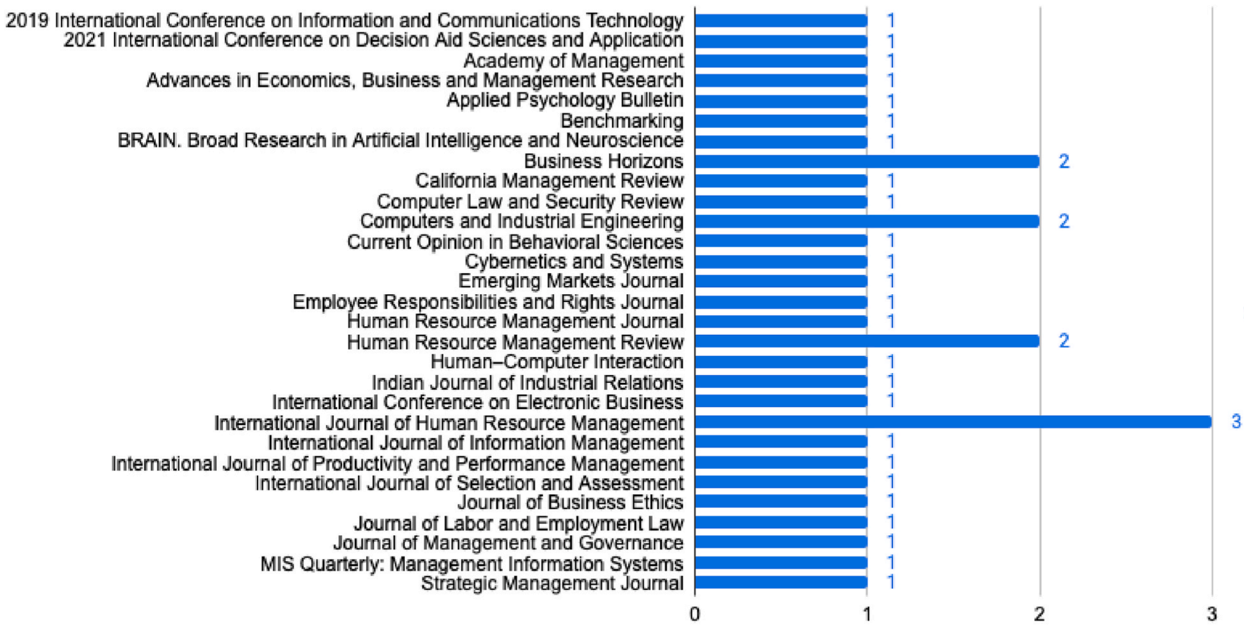

Fig. 6. Articles per journal.

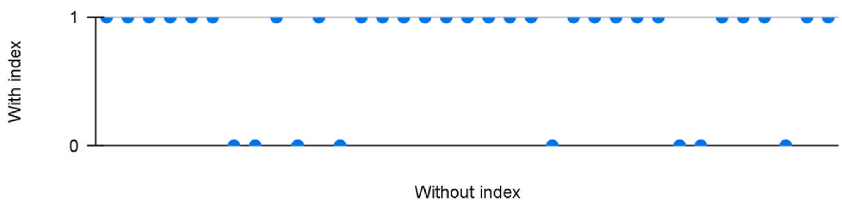

Fig. 7. Articles with indexes vs without indexes.

computer science and database research. Author affiliations in publications are provided in a variety of ways. We examined the publication author affiliations to identify the influential organisations and countries that contributed to our research. Before any studies could be performed on this data, the affiliation mentions indicating the same real-world institutions had to be aligned. We got this information from the articles. As we can observe from Fig. 12, the major contributor, as per the author affiliate's country, is the USA, with 11 articles, followed by India with 4, China, France, Netherlands and the UK with 3, Australia, Cyprus, Denmark, Germany and Turkey with 2 and Brazil, Indonesia, Ireland, Italia, New Zealand, Portugal, Romania, Slovenia, South Korea, Taiwan and Thailand with 1 article each.

In Fig. 13, the world map represents the countries with articles per affiliation country. There is a good distribution, having articles per affiliation country from North and South America, Europe, Asia and Australia. Regarding the % of contribution per affiliate country, the major contributors are the USA, with 23,4% of articles of the overall dataset, India representing 8,5%, followed by the UK,

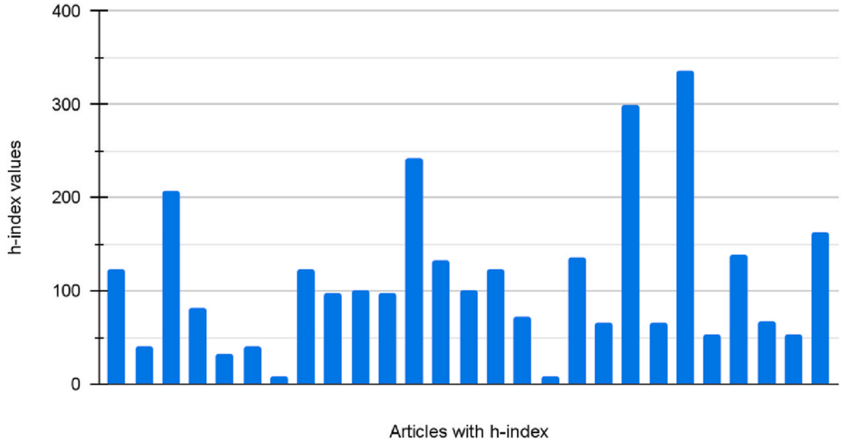

Fig. 8. h-index per article.

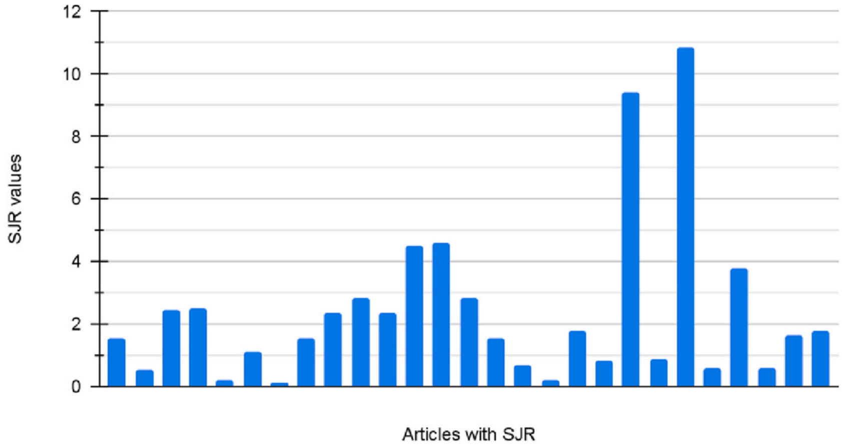

Fig. 9. SJR per article.

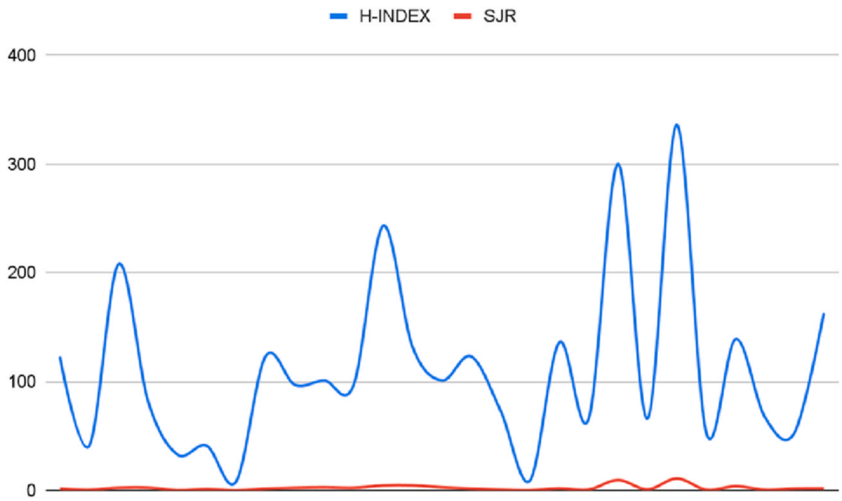

Fig. 10. h-index (top line) and SJR (bottom line) per article.

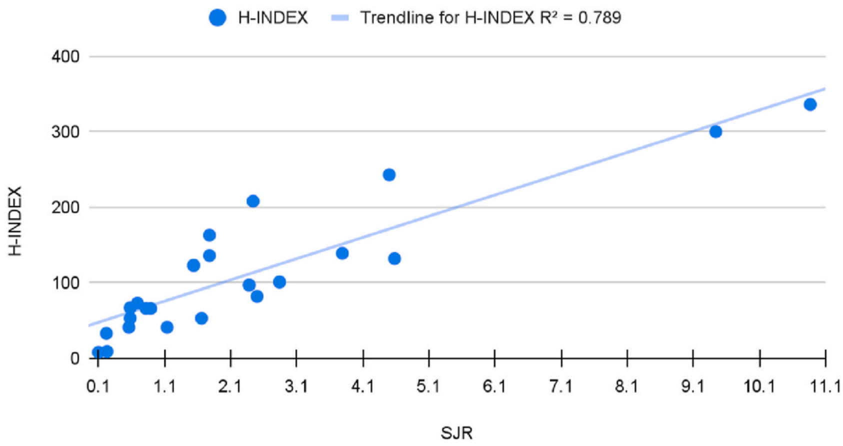

Fig. 11. Scatterplot of h-index vs the SJR indicator for the overall dataset.

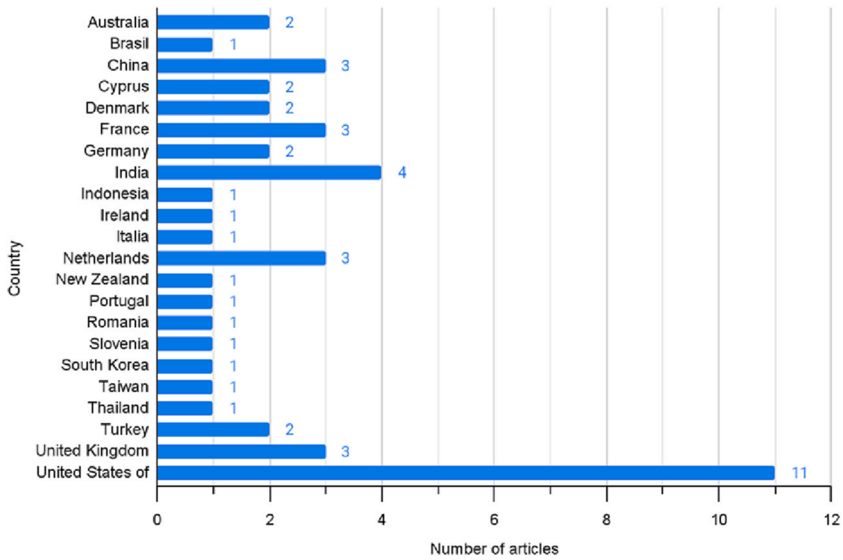

Fig. 12. Number of articles per affiliation country.

Netherlands, China and France, all with 6,4%, as depicted in Fig. 14. The colour green, from dark to light, represents the significant contributors and the red the minor contributors.

2.6.5. Citation analysis

According to Donthu et al. [82], citation analysis is a fundamental approach to science mapping that relies on the notion that citations indicate intellectual relationships formed when one publication references another. The number of citations received by a publication determines its influence. A citation is the most objective and obvious indicator of its influence. As a result, one may employ citations to examine the most prominent papers in a study topic to better grasp its intellectual dynamics. According to the Google Scholar search engine, the included articles in the systematic literature review have been referenced, ranging from 575 to 0 times. We present the ten most referenced papers in Table 8.

2.6.6. Keywords co-occurrence analysis

Keywords provided by authors of the paper that occurred more than once were enrolled in the analysis, having a total of 130 items grouped into 16 clusters. Cluster 1 with 16 items, cluster 2 with 15 items, cluster 3 with 11 items, cluster 4 with ten items, cluster 5 with ten items, cluster 6 with nine items and, from cluster 7 on, all had seven or fewer items. The links between the items are 713, and the total link strength is 742, as depicted in Fig. 16. The keywords that appeared most were "artificial intelligence", with a total link strength of 122 and "personnel management", with a total link strength of 65, both with a solid link to "employee selection" (total link strength of 49), "machine learning" (total link strength of 45) and "human capital" (total link strength of 41) (Fig. 15).

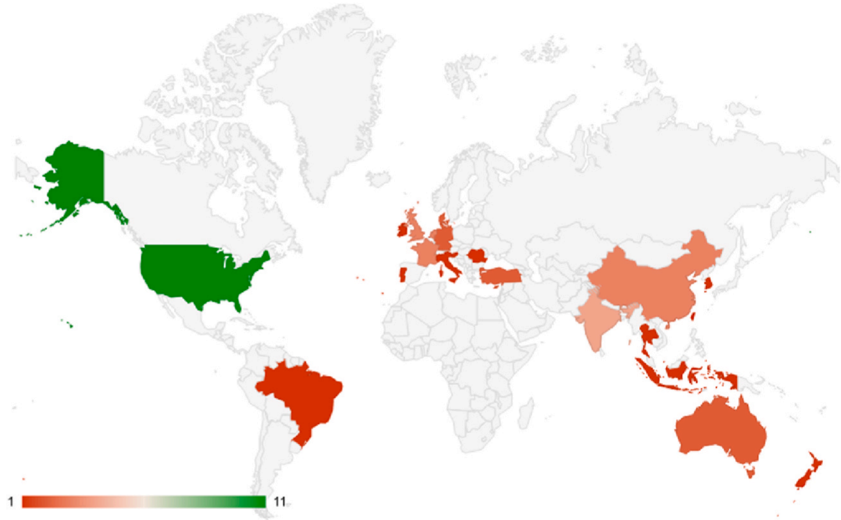

Fig. 13. World Map representing the number of articles per affiliation country.

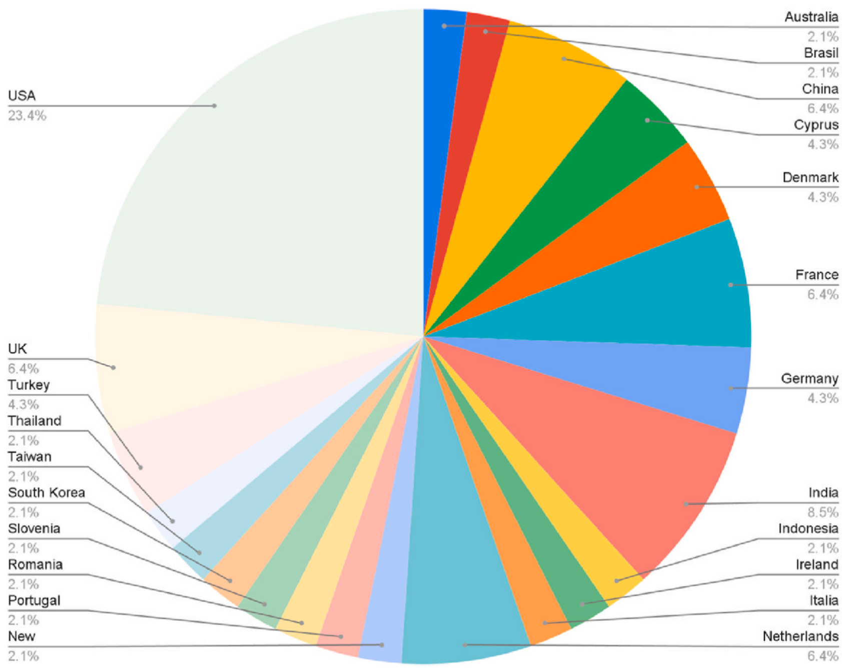

Fig. 14. % of contribution per affiliate country.

We can see the number of times a keyword appears in a circle by size in Fig. 16. The larger circles indicate that a keyword has been chosen more frequently for the selection. The most vital keywords were "artificial intelligence", "personnel management", "employee selection", "machine learning", and "human capital". The distance between the keywords shows how similar and how strong they are. Circles of the same colour indicate topic similarity and related topic relative strength. We can observe the co-keyword network based on the occurrences and average publication per year scores, between 2019 and 2022, in Fig. 17.

The Link column, listed in Table 9, denotes a relationship between the co-occurrence of two keywords. Each link has a strength, represented by a positive numeric value. The stronger the relationship, the higher this value. The properties Link and Total Link Strength for a specific item show, respectively, the number of links an item has with other items and the overall strength of those links.

2.6.7. Co-authorship analysis

The author collaboration network is graphically depicted in Figs. 18 and 19, based on the 35 articles elected, contributed by 103

Table 8
Top ten articles per citation count.

#	Article Title	References	# Citations
1	Artificial intelligence in human resources management: Challenges and a path forward.	[24]	575
2	The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions.	[62]	243
3	Artificial intelligence, robotics, advanced technologies, and human resource management: a systematic review.	[31]	224
4	A conceptual artificial intelligence application framework in human resource management.	[23]	121
5	The datafication of talent: How technology is advancing the science of human potential at work.	[72]	110
6	Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organisations.	[26]	105
7	Designing fair AI for managing employees in organisations: a review, critique, and design agenda.	[78]	97
8	Machine learning and human capital complementarities: Experimental evidence on bias mitigation.	[80]	97
9	Talent management in the manufacturing system using a fuzzy logic approach.	[73]	85
10	Justice perceptions of artificial intelligence in selection.	[79]	63

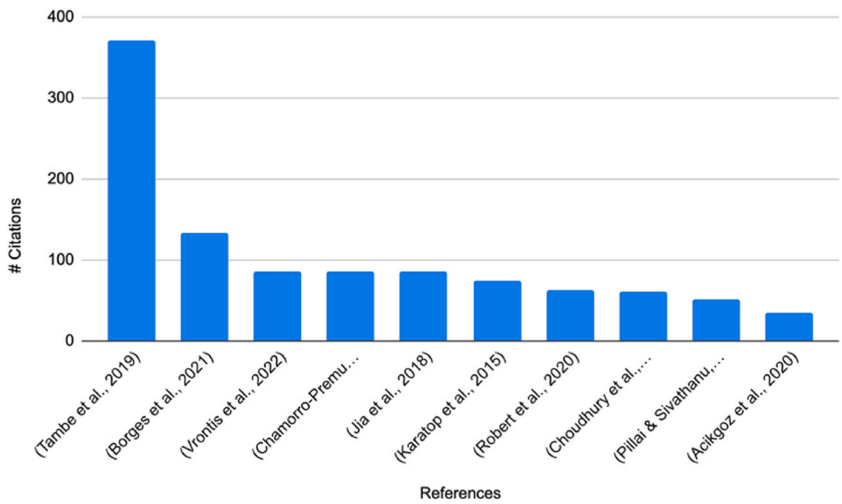

Fig. 15. Top ten articles per citation count.

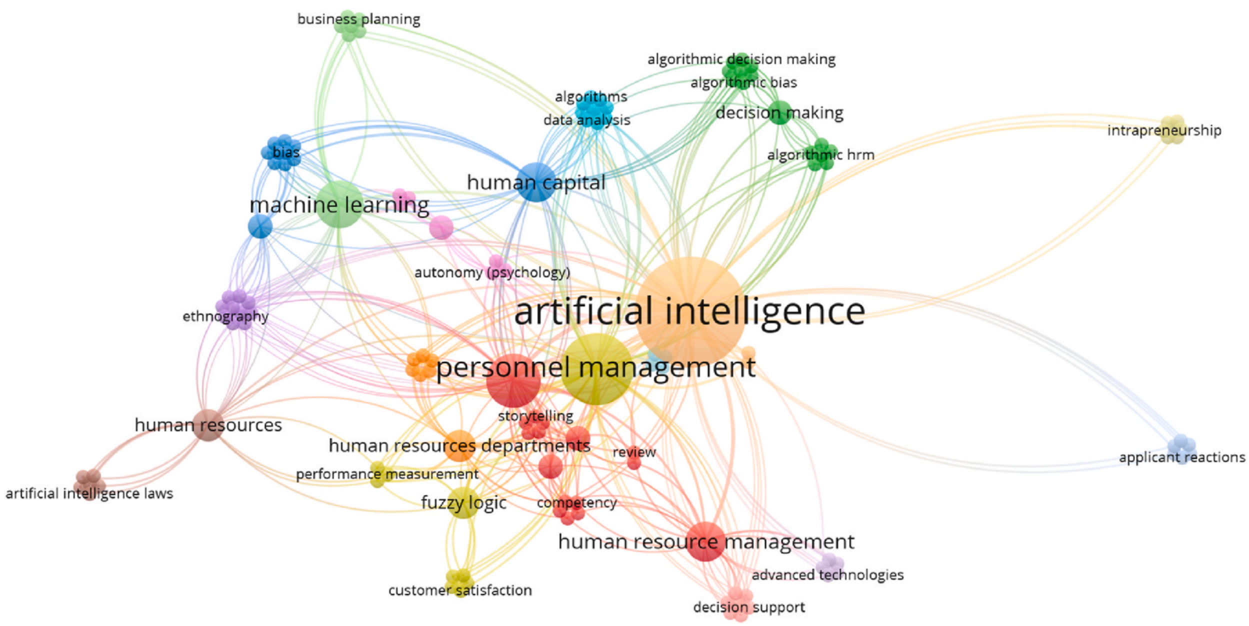

Fig. 16. Co-keyword network visualisation, based on occurrences.

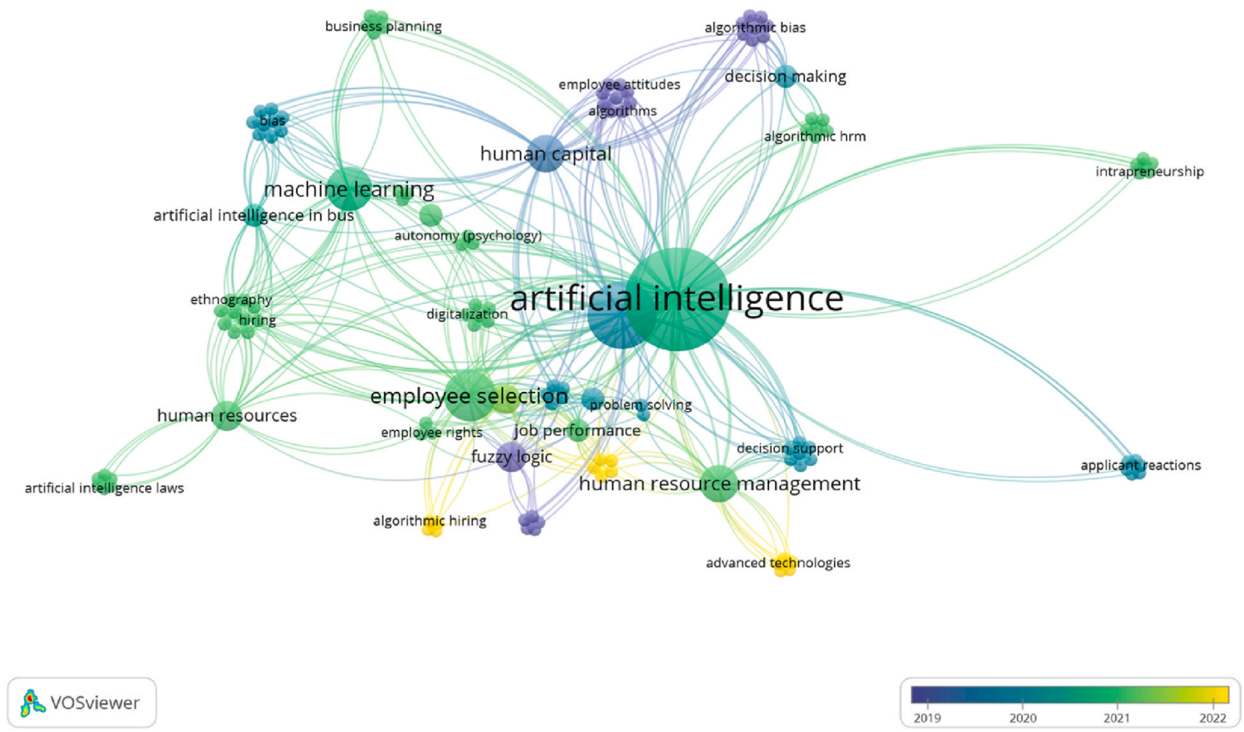

Fig. 17. Co-keyword network visualisation, based on the occurrences and average publication per year scores between 2019 and 2022.

Table 9
Link and Total Link Strength of the top 10 occurrence keywords.

#	Keyword	Cluster number	Link	Total Link Strength	Occurrence
1	Artificial intelligence	8	101	122	16
2	Personnel management	4	54	65	9
3	Employee selection	1	41	49	6
4	machine learning	9	42	45	5
5	Human capital	3	40	41	4
6	Human resources	10	26	27	3
7	Artificial intelligence in business	3	24	25	2
8	Human resources departments	7	22	25	3
9	Fuzzy logic	4	21	22	3
10	Job performance	1	17	18	2

unique authors, creating 34 clusters with 132 links and total link strength of 135.

The most extensive set of connected authors consists of 7 authors, Pereira Vijay, Vrontis Demetris, Hadjielias Elias and Christofi Michael for cluster 1, and Trichina Eleni, Tarba Shlomo and Makrides Anna for cluster 2, as depicted in Fig. 20, with 18 links and a total link strength of 21.

Table 10 shows the top ten authors, listed by several documents and the total link strength from the overall dataset, arranged alphabetically.

3. Results and discussion

The discussion focuses on the three categories stated before, engaged throughout this research, which are critical to providing a good grasp of the environment and background on the research undertaken in these areas. Similarly, these subjects will enable us to recognise and achieve the objectives to answer the research questions.

3.1. AI and human resource management

International corporations use AI technologies widely to manage talent acquisition tasks. However, adoption varies significantly from organisation to organisation [26] as most businesses need help to develop their data analytics capability [24]. According to

Fig. 18. Co-authorship network visualisation.

Minbaeva [77], HRM needs to catch up on other management functions in deploying analytics technologies and extensive data analysis. The COVID-19 pandemic brought this aspect to light since few corporations have understood the importance of HR analytics in crisis management.

Recent studies [23,56,60,65,77] argue that the incorporation of AI in HR will aid in the analysis, prediction and diagnosis of challenges affecting organisations, allowing them to make better decisions. Organisations may improve competency and efficiency by deploying AI and analytics in HR processes such as talent acquisition. Nevertheless, according to Choudhury et al. [80], there are concerns about how AI and ML will change the nature of employment and whether they will replace human capital.

We know significant changes in how people work, and hence in organisational structures, routines, and functions, have been enabled by Information Technology. Furthermore, according to Vrontis et al. [31], the interface of Information Technology and HRM has gotten more attention as researchers have attempted to understand external rather than internal impacts on organisational operations, mainly HRM practises. Despite the benefits, there is a risk associated with technology-focused HRM. Technology should be considered a decision-support tool that complements rather than replaces HR personnel.

As HR organisations' analytics capabilities go from descriptive to diagnostic to prescriptive and predictive, the primary difficulty for HR is understanding the data to address challenges and properly assist top managers [56]. Since HRM has evolved, being recognised as a strategic contributor to the business by implementing AI technologies [25,56] organisations must implement cutting-edge HR strategies to remain competitive. These practices should shift HR away from administrative duties and into areas that help redefine and reshape the employee experience through AI technology functionalities. The right recruiting decisions and employee allocations are critical to a company's success [39,55]. Moreover, competence is the key to an employee's job performance, and a competent individual has a lot of positive experiences, and positive experiences develop confidence. The confidence generated from achievement has a favourable impact on performance.

While the influence of AI on HR and people management is impossible to forecast, as stated by Charlwood and Guenole [27], they discuss several possibilities for how AI will impact organisations, especially HRM. If we use a paradox lens to examine different situations, the authors propose that optimistic and pessimistic future visions are likely to coexist. HR practitioners must develop the necessary skills to guarantee that AI development for HR and people management has its foundations in ethics and justice. AI selection methods appeal to organisations mainly due to increased speed and efficiency improvements over traditional assessment techniques.

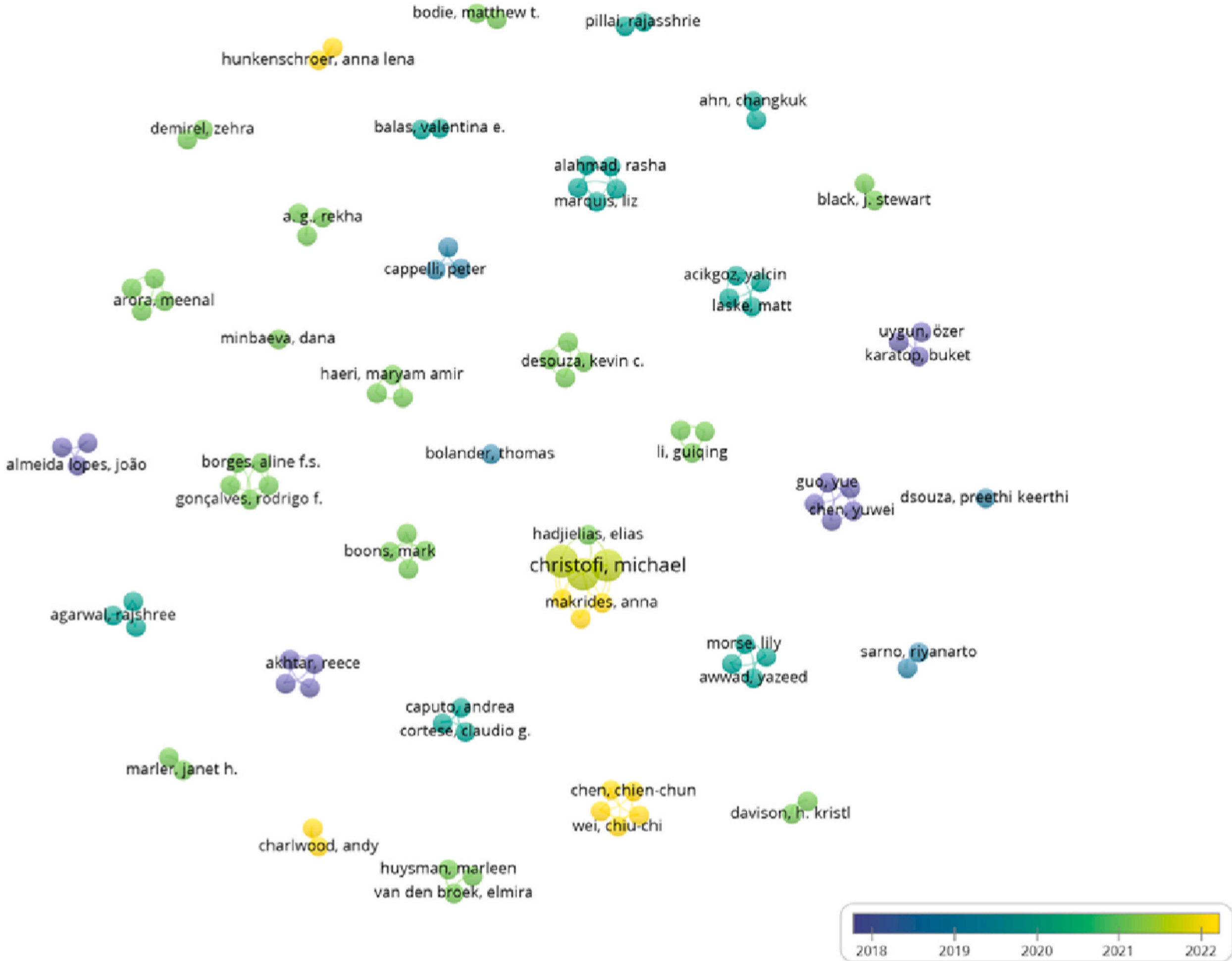

Fig. 19. Co-authorship network visualisation, based on annual publication scores between 2019 and 2022.

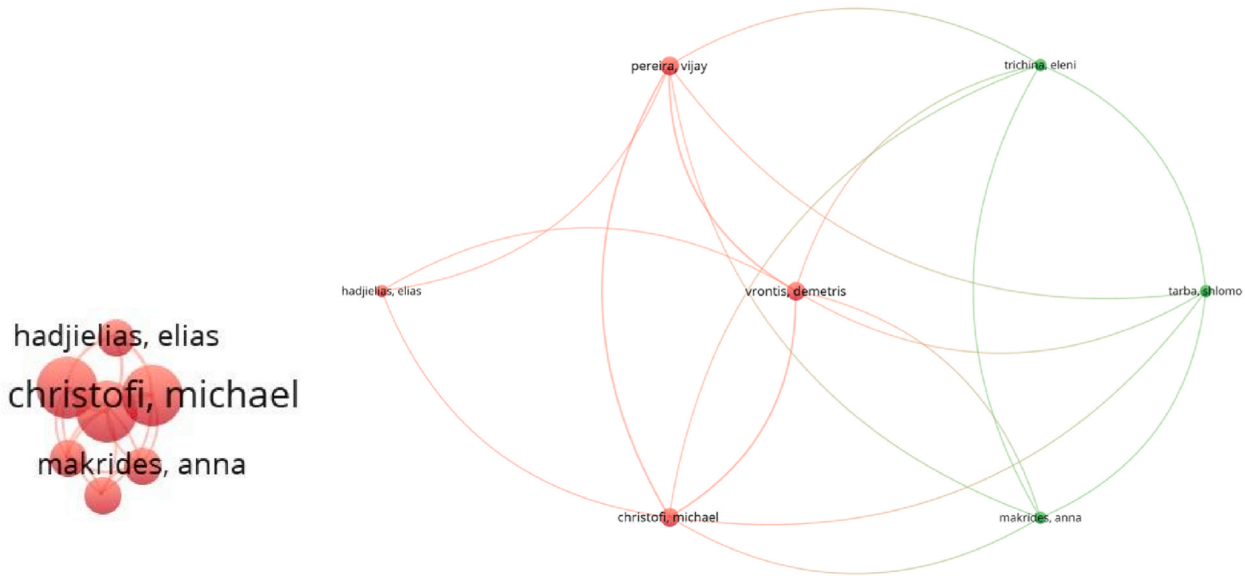

Fig. 20. Co-authorship network visualises the more extensive set of connected authors.

Table 10
Top ten author list, document number and total link strength.

#	Author	Documents	Total Link Strength
1	Christofi, Michael	2	8
2	Pereira, Vijay	2	8
3	Vrontis, Demetris	2	8
4	Makrides, Anna	1	5
5	Tarba, Shlomo	1	5
6	Trichina, Eleni	1	4
7	Alahmad, Rasha	1	4
8	Borges, Aline F.S.	1	4
9	Chen, Chien-chun	1	4
10	Chen, Su-hui	1	4

According to Hunkenschroer and Luetge [54], they are a vital asset in today's "war for talent". However, adequate infrastructure, necessary HR experience, and financial allocation of resources are essential to apply AI in HRM in enterprises effectively.

Although the capacity to swiftly learn and adapt has always been vital for leaders, it will be critical in the future of exponential technological development. As stated by Watson et al. [60], a senior leader's capacity to learn and self-develop fast will help them to go forward, adapt, and compete. This means that when it comes to picking future leaders, the potential to acquire information should precede previous expertise and experience, as leaders must grasp the significance of constantly developing new competencies; otherwise, they will be forced to make room for others. Future leaders must take responsibility for self-improvement rather than depending solely on leadership development programmes. They must be humble enough to recognise the hard and soft skills they need to learn. Then they will need to encourage themselves to keep improving using the finest tools available. Previously leaders could make most judgments based on prior experience. However, in the era of AI, leaders will need to base their decisions on the massive amount of data acquired and evaluated in real time by AI.

Recent studies [24–26] show that there are relatively few insights on a model that facilitates the Adoption of AI in HRM. There have yet to be many studies done on the model of AI adoption in HR. Moreover, AI, with its capacity to execute human duties and think and feel like humans, will eventually replace human work, and hence human interactions will become obsolete [31]. In that sense, Vrontis et al. [31] believe that the advancement of AI may alter the fundamental character of labour and constitute a severe danger to human employment. It can, however, open new possibilities for human-machine collaboration and integration. Even if AI enhances work performance and offers no immediate threat, its widespread use in HRM decision-making is likely to be viewed as a threat to human employees' autonomy, status, and job security since it can provide more alternatives and confuse people, increasing perceived complexity.

Direct uses of AI and ML in the HRM, such as the analysis and collection of digital data to complement traditional psychometric tests in evaluating talent and forecasting work-related challenges, raise various concerns about personal privacy in such a way that managers must determine how to leverage AI technology for the benefit of businesses and people in the context of global HRM [31]. Bear in mind that analytics has the potential to be a game changer, but, like any tool, organisations can use it both constructively and destructively, as stated by Minbaeva [77], exposing that the uncontrolled implementation of AI in organisations may hurt management practices, with contradictory conflicts between enhancement (a symbiotic process in which machines teach humans, and humans teach machines) and automation (decision motivated by logic and efficiency factors) in particular.

For managers, developers, and experts in the field involved in managing and developing ML in organisations, understanding machine knowledge generation as a process of reciprocal learning has practical significance [61,65,69,77,79–81].

To summarise, human resources are using data and technology to become better at making decisions and predicting future outcomes. This shift can be difficult for HR professionals, who need to understand the data and use it to help top managers solve problems. As HR has become more critical to businesses, organisations must stay up-to-date using the latest HR strategies and technologies. This strategy will help them remain competitive in the market.

3.2. AI and talent

Talent management is the main difficulty facing human capital in the 21st century [72]. Human capital cannot exist in the same way financial capital can, so management must realise that surviving the war for talent is becoming highly significant in safeguarding and generating the intangible resources that create competitive advantage [59,65].

The use of AI in HRM allows organisations to recruit and retain key talent [25,59,79]. Several studies [27,72] say that AI is still in its infancy regarding HR and people management. There are hopeful and pessimistic perspectives on how AI will affect HR and people management, which will likely coexist soon. Also, there needs to be more research on the Adoption of AI for talent acquisition from the standpoint of the organisation and HRM [23,26,72]. With just 16% of businesses employing HR technology to connect the people's side of the company to crucial organisational outputs, and maybe even fewer making data-driven choices based on those insights, the discipline of talent analytics as a whole still needs to be mature [72].

The definitions of talent are determined inside organisations, with stakeholders choosing what talent means in their specific context [57,66,71]. Through AI, the organisation does not need to pre-define goal variables. In contrast, ML algorithms may analyse data from the organisation's existing top performers to determine which candidate attributes and talent correlate with tremendous job success

[54].

Recent studies [39,67,70,71,73] applied mathematical programming to determine the ideal amount of competence elements that result in the best work performance, as well as modelling techniques to select the best mix of competence dimensions, where AI is used to create a recruitment decision model based on the results of mathematical programming and modelling techniques. The decision model is then used to make recruiting decisions by forecasting new applicant acceptance, conditional acceptance and rejection.

With enormous amounts of data, few resources, and the requirement for speed in decision-making, many businesses are encouraged to employ AI technology, primarily due to the disruptive potential displayed by top digital corporations [59,62,63,79].

In the age of massive data and the demand for speed in business, AI technologies can make better decisions than humans in some situations. However, humans can make better judgments when judgement is necessary. According to Borges et al. [62], some AI systems require a human expert in the subject area to create hypotheses and pick essential characteristics. However, the fear of job loss might cause humans to withhold beneficial knowledge from AI model building. On the other hand, deep learning algorithms can extract patterns from data independently, but the findings are complex for humans to grasp and explain.

With artificial intelligence, big data, and Internet technologies, HRM is evolving into intelligent talent management [23,58], in which emerging AI-powered recruiting tools are one of the underlying drivers that might increase talent competition. The adoption of AI for talent acquisition by HRM is a crucial study issue since it will provide HR managers with more excellent knowledge on how to use AI for talent acquisition [23,26,71].

To summarise, human resources management is changing with the use of technology such as artificial intelligence, big data, and the internet. These advancements are leading to a new way of managing talent, called intelligent talent management. One of the big benefits of these new tools is that they can help companies find and hire the best talent. Studying how HR can use these technologies is important because it can give HR managers ideas on how to improve their hiring processes.

3.3. AI bias, Ethics and Law

Different difficulties from those in other fields arise when using AI towards human resource issues, as they vary from the pragmatic to the philosophical, such as the possibility that data science findings, when used to make decisions regarding people, may seriously contradict what society regards as reasonable or acceptable [24]. According to Kim and Bodie [76], employers increasingly depend on artificially intelligent technologies to recruit, select, and manage their workforces in the workplace. Concerns exist that these systems may subject workers to discriminatory, intrusive, or otherwise unjust treatment. There still needs to be more literature focused on AI fairness [58].

Algorithms need more judgement skills. As a result, interactions between machines and humans are grounded on human assumptions, where these assumptions might be inaccurate, biased or imprecise [61,77,80]. According to several authors [68,80,81], despite the promise of AI to boost productivity, many organisations have faced substantial difficulties as a result of biases in predictions, which experts believe to be caused by biased training data or algorithms. Also, according to recent studies [68,78], the fairness of AI is being questioned and examined by academics from various disciplines, including management, law, information, data science, medical research and public policy.

Fairness in algorithmic decision-making is an important topic that raises complex legal issues and many of the law's fundamental principles into question. For millennia, philosophers have argued over the broad subject of what constitutes fairness. According to Hauer et al. [75], a society's objective must be to implement or create algorithms that make fair decisions, but the concept of fairness has several dimensions. Fairness must be mathematically specified and designed in machine learning models, which are the foundation of AI decision-making [61,75]. The application environment can precisely explain what fairness genuinely means when building AI decision-making situations.

Moreover, according to several authors [68,75,76,79], while applying AI in hiring decisions appears to have some clear advantages, there is a significant risk that it could exacerbate or even increase already-present prejudices and discriminatory effects in society. As recent studies show [68,76], employers who employ AI technologies in their HR operations should be aware of the risks of bias and take preventative measures to avoid them. Operating AI technologies requires closely examining how these tools are developed and used in a particular workplace. According to Hauer et al. [75], using AI-based recommendation systems has grown in many vital application sectors. Nevertheless, these systems must be trained using large amounts of data, which in most cases are unintentionally biased, leading to discrimination when the algorithmic is used.

The organisation must fully involve workers and stakeholders in designing and deploying AI systems for AI to be ethical. Existing methods of people management, if not regulated, according to Charlwood and Guenole [27], might lead to AI that drastically limits worker autonomy while increasing effort and stress. If this kind of AI is to be limited, the HR profession's ethical ideals and practical insights are critical.

Managers must be cautious about mitigating biases from machine learning technology to realise productivity gains [68,80]. One such discrimination occurs when the machine learning tools receive incomplete inputs [24,80,81]. Under such conditions, those tools can produce forecasts that are poorer than those produced by earlier generations of technology. AI can minimise bias but is never totally devoid of prejudice and entails the possibility of algorithmic discrimination, even when programmers have no evil intentions [54].

Choudhury et al. [80] research indicate that managers should take into account two human capital characteristics, domain knowledge and the vintage specific skills (abilities developed via a past acquaintance of tasks with the technology) to ensure that productivity gains of machine learning are achieved, by addressing the incompleteness of the input to the machine learning tools. According to Tambe et al. [24], managers should be required to share their assumptions when using AI in HR since such beliefs are then included in the algorithms and analyses.

Moreover, according to Hunkenschroer and Luetge [54], despite significant research on AI recruiting in recent years, a complete ethical understanding of recruiting as a growing application context of AI still needs to be improved. Businesses must understand both the benefits and possible threats that AI recruiting technology may bring and how algorithmic results may contradict what they wish to achieve.

In the context of HRM, ML aims to produce predictive analytics that can assist HR managers in making better decisions on the management of human resources. Moreover, machine learning projects are unlikely to be undertaken by smaller firms due to the cost of gathering and analysing these additional sources of data [74]. However, the availability and diversity of data have increased over the past ten years, which has expedited the use and applicability of machine learning technology leading to a potential loss of privacy, the most critical ethical worry regarding machine learning.

Although ML can potentially improve organisational productivity, it is critical to ensure that people are treated fairly when touched by the AI process, which can sometimes occur [78]. Recent studies [74,76] note that enforcing privacy issues legally differs significantly worldwide. Europe's reaction to privacy issues is taken care of by the enforcement of the GDPR (General Data Protection Regulation), which provides an alternate paradigm, explicitly targeting AI decision-making by demanding the transparency and limitation of automated decision systems, as well as allowing data subjects to opt out of wholly automated profiling. It still needs to be determined how effective GDPR will be in limiting the use of predictive AI.

The use of AI in Recruitment and Selection procedures frequently involves the application of GDPR articles 9 and 22, which target the processing of specific categories of personal data, forbidding the processing of genetic data, biometric data used to uniquely identify a natural person, health data, or data about a natural person's sex life or sexual orientation, as well as the processing of personal data which might reveal political opinions, religious or philosophical beliefs or racial or ethnic origin [65].

However, as noted by Hamilton and Davison [74], employees have different comprehensive rights to privacy in all parts of the world. As it may transgress any of the dimensions of justice, the use of ML in organisations has the potential to be unethical. It is feasible for ML software to disregard procedural justice standards since it incorporates software that makes conclusions regarding data, presumably without human participation. Fair practices include, among other things, safeguards against bias, correct information usage, giving people a chance to be heard, and consistent execution of standards.

As AI becomes increasingly integrated and relevant in organisations, the law will need to evolve to effectively avoid discrimination, safeguard privacy, and address potential threats of employee discrimination [65,76]. As a result of how algorithmic decision functions differently from human judgment, the evaluation of discrimination moves from process-oriented to result-oriented, as stated by Hauer et al. [75]. Considering this transformation, society must choose the appropriate form of fairness for each situation.

To summarise, as AI becomes more common in organisations, the laws and regulations will need to change to protect people from discrimination and protect their privacy. With AI making decisions differently than people do, it is important to look at the results of those decisions to make sure they are fair and just. Society will need to decide the best way to ensure AI decisions are fair in different situations. Artificial intelligence has the potential to make things more efficient and productive, but it can also cause problems. One big issue is that the predictions made by AI systems can be biased, which can happen if the data or algorithms used to train the system are not fair. This means that the interactions between people and machines are based on human assumptions, which might not always be correct. Many experts from different fields, including management, law, and data science, are now looking at how to make sure AI systems are fair and unbiased.

4. Conclusions

This comprehensive literature review aims to uncover the knowledge gaps in the application of AI for potential and talent identification within organisational settings. Our systematic and in-depth analysis of relevant studies and publications highlights the linkages between AI and HRM. It underscores the fact that research in this area is still in its early stages. Our findings, based on a robust methodology, reinforce and build upon the previous research that recognises the potential benefits of utilising AI in HR, offering valuable insights from an organisational perspective.

RQ1) How can AI models be used to evaluate employee potential? Organisations are recognising the critical role of talent management in gaining a competitive edge, particularly with the growing demand for higher-level skills in the knowledge-based economy. However, despite the advantages of using AI for talent acquisition, not all HR managers have adopted this technology. This is due to a lack of knowledge and skills in HR data analysis, limited organisational support, unavailability of structured information, and resource constraints. To address these gaps, HR managers must proactively acquire knowledge of AI and its benefits for HRM. They have a crucial role in bridging the technological, human, societal, and governmental divides and ensuring that AI effectively deploys while minimising risks and promoting favourable employee outcomes. There is a need for more research on implementing AI-based applications in HRM, and organisations must invest in developing their HR professionals to utilise AI technology effectively.

RQ2) How effective are AI models in talent identification? The potential for AI and machine learning to uncover new insights from data is significant, and algorithms may provide superior perspectives compared to human experts. The impact of AI on the future of work and organisational structures is undeniable, and it is crucial to remember that humans play a critical role in the entire process. The acceptance and successful implementation of algorithms can be facilitated when individuals have a voice in shaping the outcomes.

RQ3) How do AI models bias talent identification? AI can potentially violate ethical and legal standards, making it imperative for HR professionals to work closely with data scientists and gain a thorough understanding of data analytics to prevent such breaches. HR must be aware of the variables in the datasets and, where applicable, the variables used in the machine learning algorithms. Unsupervised learning is one type of machine learning that can pose specific risks, as the variables used to train the algorithm are determined by the software rather than being selected by data scientists, which may result in adverse outcomes. HR managers should ensure that ML initiatives are free from bias when improving the organisation and its employees. By adopting a continuous improvement approach, ML initiatives are more likely to be accepted and provide a fairer and more positive workplace environment, provided that legal, ethical, and employee rights are adequately addressed. The success of algorithms depends on employee engagement in developing and implementing these initiatives, and machine learning can help address pre-existing biases by promoting fairness and transparency.

4.1. Research managerial implications

This systematic literature review highlights the critical factors in using AI for talent and potential evaluation. Our findings significantly impact managers and policymakers in linking AI and Human Resource Management. Based on the research, managers can gain a deeper understanding of how to integrate AI effectively into HR practices, allowing them to make informed decisions and improve their processes. As HR plays a crucial role in bridging technical, human, social, and governmental gaps, HR managers must proactively understand the benefits and potential risks of incorporating technology into HR processes. By doing so, they can support the efficient deployment of AI while minimising risks and promoting positive employee outcomes.

4.2. Research theoretical implications

Our findings indicate connections between AI and HRM literature, implying that associated research is still in its early phases. Our findings are consistent with previously published research that acknowledges the benefits of employing AI in HRM in terms of growing the corpus of knowledge, primarily from an organisational perspective. This research helps organisations and managers comprehend the advantages of utilising technology in human resources.

4.3. Limitations and recommendations

While our study has conducted a comprehensive review of peer-reviewed publications from various databases, it is essential to acknowledge that it has some limitations. Only peer-reviewed publications from the databases EBSCO Academic Search Complete, EBSCO Business Source Complete, ERIC, EBSCO Library, Information Science & Technology Abstracts, and Regional Business News are included in our dataset, proving comprehensive coverage. EBSCO aggregates nearly 400 research databases. Our review, however, does not contain book reviews, working papers, or conference proceedings due to our strict exclusion criteria, which have certain inherent limitations. Future studies could be improved by having inclusion criteria to address publications from book reviews, working papers, conference proceedings and papers written in other languages besides English.

Future research should build upon the ground breaking insights uncovered in our study by exploring the development of advanced AI models that can empower managers and other key players within organisations to gain a comprehensive and nuanced appreciation of the potential benefits and risks associated with AI. Future studies could also explore innovative AI strategies to improve competitiveness, build human capital, and implement organisational policies.

4.4. Contributions

Our study makes a significant contribution to the growing body of knowledge on AI in Human Resource Management, potential evaluation, and talent identification. Our findings provide valuable insights and a foundation for future research to build upon, exploring new and innovative avenues in the field. Additionally, our study serves as a valuable tool for academics to analyse the evolution and advancement of AI in HRM.

Author contribution statement

T.França: Conceived and designed the experiments; Performed the experiments; Analysed and interpreted the data; Contributed reagents, materials, analysis tools or data; wrote the paper.

H. São Mamede: Conceived and designed the experiments; Performed the experiments; Analysed and interpreted the data; Contributed reagents, materials, analysis tools or data.

J. Barroso: Conceived and designed the experiments; Performed the experiments; Analysed and interpreted the data; Contributed reagents, materials, analysis tools or data.

V. Santos: Conceived and designed the experiments; Performed the experiments; Analysed and interpreted the data; Contributed reagents, materials, analysis tools or data.

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Data availability statement

Data included in article/supp. material/referenced in article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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